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Betting Market Inefficiencies in European Football – Bookmakers' Mispricing or Pure Chance?

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Abstract

Research on sports betting often identifies biased evaluation by bookmakers and corresponding opportunities for profitable strategies to bettors. Such studies repeatedly provide evidence for the existence of biased betting odds for different periods and leagues, leaving the impression that inefficiencies are very common. Since most studies cover only a few seasons, the question remains whether these market inefficiencies persist over time. We review the literature on the big five leagues in European association football and then analyse 14 seasons to detect the occurrence and duration of betting market inefficiencies. While our results replicate the temporal findings of previous research, they also show that biases do not persist systematically over time and across leagues. Furthermore, a Monte Carlo simulation reveals that the number of inefficient periods barely exceeds what would be expected in an efficient market.

Keywords: Betting Markets, Biases, Market Efficiency, Monte Carlo Simulation

1 Introduction

On a yearly basis, more than 10 billion-euro turnover is generated from legal sports betting in Europe alone as reported by the European Gaming and Betting Association for 2018. Millions of bettors worldwide predict the outcome of sporting events and presume to have better knowledge about the expected outcome of the game than bookmakers, who offer odds prior to the kick-off and in-game. To secure profitability, betting markets have to be excellent predictors of game outcomes and (similar to other financial markets) contain all information available to be efficient (Fama, 1970). In financial markets, efficiency implies that market participants cannot use strategies to beat the market and profit financially. Transferred to sports betting, market efficiency implies that betting odds (the assets) reflect all available information. Accordingly, there are no systematic strategies that would enable bettors to generate positive returns (Thaler and Ziemba, 1988).

Research on betting markets follows the concept of efficient markets in testing various strategies for profits. Such strategies typically classify team or game characteristics and include systematically betting on (e.g.) home teams, underdogs, or promoted teams. Previous studies have tested such simple strategies using one or multiple season(s) of data and have uncovered inefficient odds for different leagues and periods. Since most studies present only a snapshot of relatively short periods of time, it remains to be investigated whether market inefficiencies are systematic and persist over time, or whether their appearance is of temporary and random nature. For the latter case, previous results uncovering short periods of inefficiencies may simply be driven by statistical noise.

A second motivation to keep investigating betting markets stems from the development of the market itself. The introduction of online betting enabled bettors to put their money with bookmakers outside of their local market. Hence, they can now easily compare odds from different bookmakers online at low search costs. Bettors benefit from this increased competition since bookmakers' margins decreased. As a consequence, bookmakers have increased their forecast precision to remain profitable despite facing increasing competition (Forrest et al., 2005; Štrumbelj and Šikonja, 2010). Given such growing competition in recent years, the question if profitable strategies arise comes up.

This paper contributes in three ways: (1) we provide an overview on the literature regarding biased betting odds in (association) football, (2) empirically analyse all major European football leagues towards these biases for more than a decade of seasons, and (3) discuss the existence of long-term biases in named betting markets. Regarding (2) and (3), we investigate the short- and long term profitability of popular betting strategies and provide an overview on potential inefficiencies. Our analysis covers 14 seasons from 2005/06 to 2018/19 for the five major European football leagues, namely the English Premier League, the French Ligue 1, the German Bundesliga, the Italian Serie A, and the Spanish La Liga.

We can replicate betting market inefficiencies from previous studies, but show that most of these strategies do not generate positive returns in the long run. Furthermore, a simulation based analysis provides evidence that most of these findings can be easily caused by chance and statistical noise, therefore further challenging the persistence of systematic biases over time.

The paper is organised as follows. In the next section we cover the literature which reports inefficient betting markets in European football. In Section 3, we describe our extensive data and provide exploratory analysis. Section 4 covers the empirical analysis and discusses profitable strategies for all leagues considered. Furthermore, we conduct a simulation based analysis on alleged biases appearing by chance under full market efficiency. Section 5 discusses our major findings and provides points for further research.

2 Literature review

Research on (in)efficiencies and biases in betting odds has a rich tradition and has been mainly published in forecasting, operational research, and general economic outlets. Sports betting markets are financial markets, as a bet on a team is equivalent to buying a stock in a company (Sauer, 1998). The typical approach in analysing market inefficiencies is to provide profitable strategies. Such strategies exploit inefficient information processing by bookmakers, which result in biased betting odds. This section reviews research on top division European football, as the empirical part of this paper is devoted to the longevity of inefficiencies in such leagues. As it stands, the biases presented in this section have most commonly been researched[1] and are analysed in the empirical section of this paper.

The *favourite-longshot bias* reflects the tendency of bettors to overvalue underdogs and undervalue favourites, potentially as a result of risk preference (Snowberg and Wolfers, 2010). Bookmakers could deviate the actual betting odds away from the fair odds and offer lower returns on underdogs and higher returns on favourites. If such deviation is large enough, bettors can generate positive returns on investment (ROI) by simply betting on favourites. Several studies provided evidence for the existence of the favourite-longshot bias in European football (see, e.g., Direr, 2011; Rossi, 2011; Vlastakis et al., 2009; Angelini and De Angelis, 2019). The *reverse favourite-longshot bias* inversely suggests undervalued underdogs and positive returns when betting on them. Such reverse favourite-longshot bias was found by, e.g., Deschamps and Gergaud (2007).

While the location of the game can decide which team is declared to be the favourite, the *home bias* refers to increased (lowered) payouts for the home (away) team compared to the fair odds. If the bias is large enough, a profitable strategy would suggest to systematically bet on the home team. Evidence on the existence of biased betting odds towards away teams has been provided by, e.g., Angelini and De Angelis (2017), Forrest and Simmons (2008), and Vlastakis et al. (2009).

Biased odds can also result from bettors' sentiment, referred to as *sentiment bias* in the literature. Here, betting odds are found to be biased towards the more popular teams, resulting in positive returns when betting on them. Papers that find the sentiment bias include Forrest and Simmons (2008) as well as Franck et al. (2011).

Previously cited work analyses multiple years of data to find systematic biases. Still, there is reason to believe that betting markets' efficiency can vary over time and within seasons. Due to the structure of leagues, competition can be split into seasons and seasons can be split into different periods. Since contracts in professional sports run only for few seasons and transferring players is very common, teams usually experience many roster changes during the off-seasons, making seasons a natural candidate to split.

[1] As the paper covers pre-game odds, the literature overview also covers work on pre-game data only.

In line with this, some papers split seasons into different parts to detect temporal betting market inefficiencies. Goddard and Asimakopoulos (2004) find temporal inefficiencies at the very start and end of seasons. Deutscher et al. (2018) discover positive returns for betting on recently promoted teams at the start of seasons.

While several studies analyse data covering multiple (but few) seasons, others run their analysis season by season. Only a limited number of studies split observation periods within seasons. The overview given in Table 1 supports the idea that inefficiencies can be temporarily detected for various leagues. Still, the literature does neither offer an overview on the persistence of biases over time, nor can put it into perspective if positive returns to bettors occur more often than expected under full market efficiency. One could make a case that inefficiencies get reported and published more often than analyses that find markets to be efficient (as expected by theory). Such mechanism, i.e. a higher barrier to publication for studies that produce null results, is observed in different fields and labelled as publication bias (Franco et al., 2014). Accordingly, a literature review might suggest betting markets to be inefficient on a regular basis while such impression could be driven by the selective reporting of inefficiencies.

Table 1: Overview of studies covering betting market inefficiencies.

authors & year	seasons	ENG	FRA	ITA	GER	ESP	full sample	season splits	within-season split	home	FLB	sentiment	promoted	profitable strategies
Pope and Peel (1989)	1981-1982	✓	✗	✗	✗	✗	✓	✗	✗	✓	✓	✗	✗	-
Cain et al. (2000)	1991–1992	✓	✗	✗	✗	✗	✓	✗	✗	✗	✓	✗	✗	Betting on heavy favourites
Kuypers (2000)	1993–1995	✓	✗	✗	✗	✗	✓	✗	✗	✗	✗	✓	✗	Betting as suggested by model
Cain et al. (2003)	1992–1993	✓	✗	✗	✗	✗	✓	✗	✗	✗	✓	✗	✗	Betting on heavy favourites
Dixon and Pope (2004)	1993–1996	✓	✗	✗	✗	✗	✓	✓	✗	✗	✓	✗	✗	-
Goddard and Asimakopoulos (2004)	1990–2000	✓	✗	✗	✗	✗	✓	✓	✓	✗	✓	✗	✗	Betting early and late season
Deschamps and Gergaud (2007)	2002–2006	✓	✗	✗	✗	✗	✓	✓	✗	✓	✓	✗	✗	Betting on heavy underdogs
Forrest and Simmons (2008)	2001–2005	✗	✗	✗	✗	✓	✓	✗	✗	✓	✗	✓	✗	Betting on popular teams
Graham and Stott (2008)	2001–2006	✓	✗	✗	✗	✗	✓	✓	✓	✓	✓	✗	✗	-
Vlastakis et al. (2009)	2002–2004	?	?	?	?	?	✓	✗	✗	✓	✓	✗	✗	Betting on heavy favourites (especially in away games)
Direr (2011)	2000–2011	✓	✓	✓	✓	✓	✓	✓	✗	✗	✓	✗	✗	Betting on heavy favourites
Franck et al. (2011)	2001–2008	✓	✗	✗	✗	✗	✓	✗	✗	✗	✓	✓	✗	Betting on popular teams
Rossi (2011)	2007–2008	✗	✗	✓	✗	✗	✓	✗	✗	✗	✓	✗	✗	Betting on heavy favourites
Constantinou and Fenton (2013)	2005–2012	✓	✗	✓	✓	✓	✓	✓	✗	✓	✓	✗	✗	Betting on home games when home team is underdog
Flepp et al. (2016)	2011	?	?	?	?	?	✓	✗	✗	✗	✗	✓	✗	-
Feddersen et al. (2017)	2011–2013	✓	✓	✓	✓	✓	✓	✗	✗	✗	✗	✓	✗	-
Deutscher et al. (2018)	2012–2016	✗	✗	✗	✓	✗	✓	✗	✓	✓	✗	✗	✓	Betting on promoted teams
Elaad et al. (2019)	2010–2018	✓	✗	✗	✗	✗	✓	✓	✗	✓	✓	✗	✗	-
Angelini and De Angelis (2019)	2006–2017	✓	✓	✓	✓	✓	✓	✗	✗	✗	✓	✗	✗	-
Franke (2020)	2006–2014	✓	✓	✓	✓	✓	✓	✗	✗	✓	✓	✓	✗	Betting on heavy favourites (but only on betting exchanges)
This paper (2020)	**2005–2019**	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	

Note: "FLB" denotes the favourite-longshot bias.

3 Data

To provide a comprehensive long-term analysis, we rely on data from `www.football-data.co.uk` (Football Data, 2020), which cover all matches of the men's first football divisions in England, France, Germany, Italy, and Spain from season 2005/06 to 2018/19, totalling 25,564 matches. It details the actual result and the pre-game betting odds for all potential outcomes (home win, draw, and away win) of each match. As betting odds from different bookmakers are reported in our data, we rely on the average betting odds over all bookmakers that provide information. Such (average) betting odds are calculated using, on average, 42 individual bookmaker odds. The pairwise correlation in our sample (over all leagues) between betting odds offered by different bookmakers is fairly high, with at least 0.96 for home wins and 0.95 for away wins.

Descriptive statistics

For each match, we restrict our analysis to bets on the home and the away team, as odds for draws do not vary much in football (Pope and Peel, 1989). As we analyse matches from both teams' perspective, each match generates two rows in our data. This accumulates to 51,128 observations in total over all leagues and seasons considered. Based on bookmakers' odds, *Implied probabilities* $\hat{\pi}_i$ for each outcome are calculated as

$$\hat{\pi}_i = \frac{1/O_i}{1/O_h + 1/O_d + 1/O_a}, \quad i = h, d, a$$

with odds O_i, $i = h$ for a home win, $i = a$ for an away win, and $i = d$ for a draw. Figure 1 (left panel) shows boxplots of the *Implied probabilities* for home and away wins, which indicate higher implied probabilities for home than for away teams. This is in-line with the home field advantage as suggested by the higher proportion of home wins found in our sample: we find home teams to win about half of the matches (46.18%), whereas away teams win only about every fourth match (28.04%, see Table 2). These percentages vary only slightly across leagues.

To take into account these differences between bets on home and away teams, we introduce the covariate *Home* taking value one for bets on the home team. Since existing studies shown in Table 1 revealed a potential sentiment bias, we further consider the

Table 2: Summary statistics on home wins, away wins, and promoted teams' games (2005/06–2018/19).

	England	France	Germany	Italy	Spain	Total
observations	10,640	10,640	8,568	10,640	10,640	51,128
home win (%)	4,962 (46.6)	4,800 (45.1)	3,884 (45.3)	4,906 (46.1)	5,058 (47.5)	23,610 (46.2)
away win (%)	3,054 (28.7)	2,820 (26.5)	2,524 (29.5)	2,912 (27.4)	3,024 (28.4)	14,334 (28.0)
promoted (%)	2,856 (26.8)	2,796 (26.3)	2,104 (24.6)	2,856 (26.8)	2,856 (26.8)	13,468 (26.3)

difference in mean attendance between the two opponents in the corresponding season as a proxy for the sentiment. Since we include two observations per match, the distribution is symmetric around zero. Figure 1 (right panel) shows only positive values for all leagues. The leagues considered can be broadly categorised into two groups. Whereas for the Spanish, English, and German league the median absolute difference in attendance is around 15,000 and the maximum difference is around 70,000, for the French and Italian league the median absolute difference is around 10,000 and the maximum around 50,000. To account for differences in the effect of betting on and against promoted teams in both home and away games, we introduce the four binary variables *OnPromotedHome*, *OnPromotedAway*, *AgainstPromotedHome*, and *AgainstPromotedAway*. We identify 26.3% of all games to include one promoted team (see Table 2). Matches between two promoted teams are treated as if no promoted team participated. As the number of promoted teams differs by league and season, this proportion varies slightly across time.

To ensure that biases do not interfere, Table 3 displays the correlation coefficients between the covariates for all biases considered. The highest correlations exist between the *Implied probability* and *Home* as well as between the *Implied probability* and *DiffAttend*, indicating that home teams and teams with a large fan base are often declared to be the favourite. The correlation between all other covariates is fairly low (see Table 3).

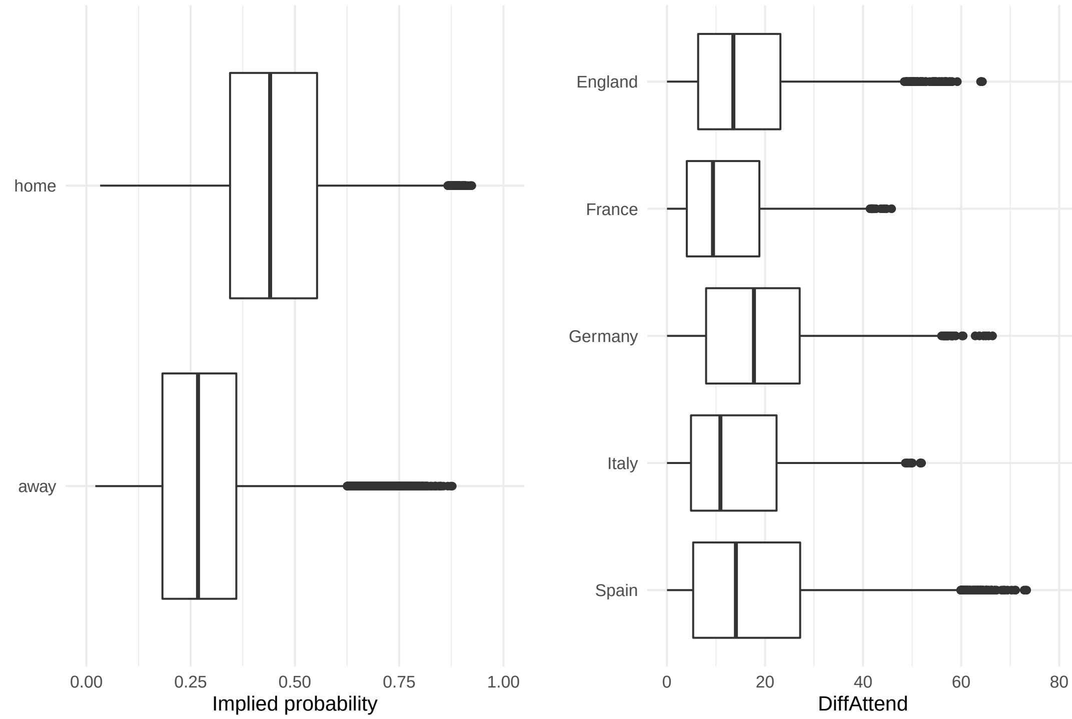

Figure 1: Boxplots on the probability as implied by bookmakers' odds (left panel) and boxplots on the differences in the attendance (right panel).

Table 3: Correlation matrix of the covariates for the *Implied probability*, the *Home* bias, the sentiment bias (*DiffAttend*), and the promoted team bias (*OnPromHo.*, *OnPromAw.*, *AgPromHo.*, *AgPromAw.*).

	ImpliedProb.	*Home*	*DiffAttend*	*OnPromHo.*	*OnPromAw.*	*AgPromHo.*	*AgPromAw.*
ImpliedProb.	1	0.452	0.639	−0.048	−0.268	0.290	0.025
Home		1	0	0.266	−0.266	0.266	−0.266
DiffAttend			1	−0.122	−0.122	0.122	0.122
OnPromHo.				1	−0.070	−0.070	−0.070
OnPromAw.					1	−0.070	−0.070
AgPromHo.						1	−0.070
AgPromAw.							1

Market development over time

As argued in the Introduction (and as shown by Forrest et al., 2005, and Štrumbelj and Šikonja, 2010), margins are expected to decrease over time. Figure 2 shows the average margins calculated as $\frac{1}{M}\sum_{m=1}^{M}\left(\sum_{i\in\{h,d,a\}} O_{m,i}^{-1} - 1\right)$ for matches $m = 1, \ldots, M$ from seasons 2005/06 to 2018/19 (left panel). In all leagues covered, average margins decreased from more than 10% at the start of our observation period to about 5% in recent years.

The left panel in Figure 2 also indicates systematic differences in the margins between different leagues. To remain profitable despite decreasing margins, bookmakers would have to improve their predictive power. We investigate this assumption by considering the Brier score (Brier, 1950), which is given as

$$\frac{1}{n}\sum_{i=1}^{n}(\hat{\pi}_i - y_i)^2,$$

where $\hat{\pi}_i$ denotes the implied probability of bet i according to the bookmakers' odds and y_i indicates whether the bet won ($y_i = 1$) or lost ($y_i = 0$). Perfect predictions would lead to a Brier score of 0, while Brier scores increase in the inaccuracy of predicted game outcomes. To evaluate the predictive power over time, Figure 2 (right panel) provides the Brier scores for all leagues contained in our data.

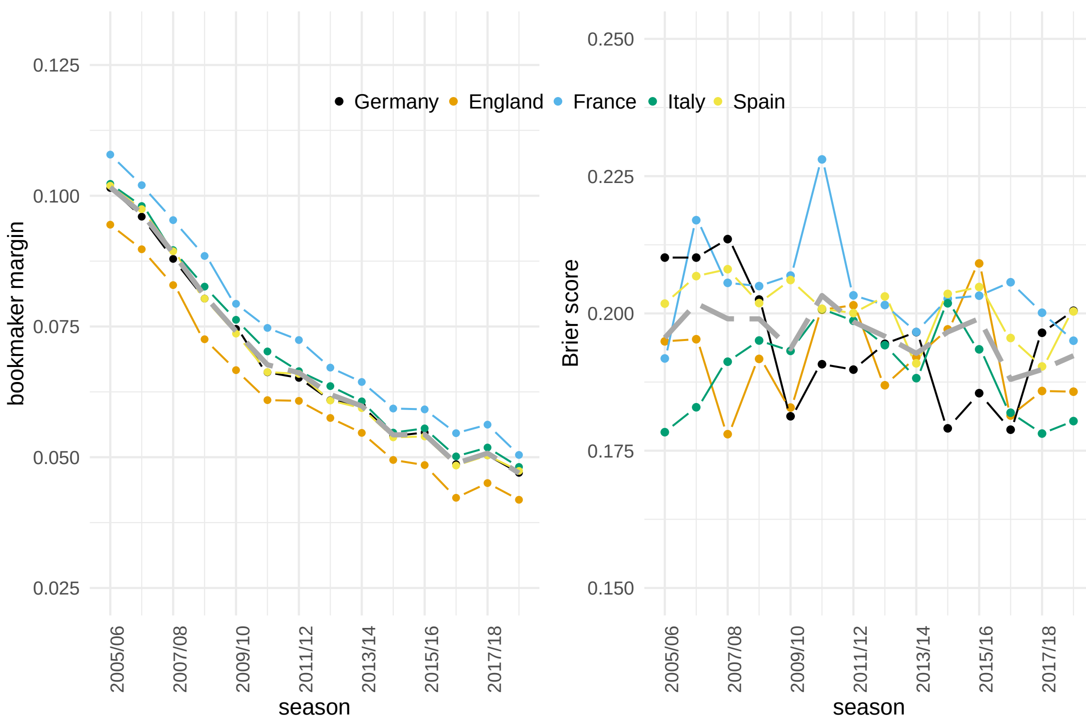

Figure 2: Bookmakers' margins and Brier scores during the period observed (season 2005/06 until 2018/19). Colours indicate different leagues, and the grey dashed lines show the average over all leagues.

Indicated by the grey dashed line, Brier scores over all leagues improved only slightly over time. Comparing both panels in Figure 2, we observe that relatively high (low) Brier scores co-occur with high (low) margins, e.g. for France in 2010/11. Jumps in the Brier score are observable in all leagues considered, indicating that the predictive power of bookmakers' odds varies considerably between seasons. This, in turn, opens opportunities for profitable strategies at times when the predictive power of betting odds is rather low. It becomes even more relevant for recent seasons, as the margins decrease faster over time than the Brier scores (see both panels of Figure 2).

4 Analysis

Given the developments of betting markets discussed above and the number of publications revealing betting market inefficiencies for various seasons, we seek to explore whether biases persist over a longer period, whether any of these are profitable in the long run and how likely such findings would be in an efficient betting market. We first introduce our methodological approach and investigate the different biases discussed above for the English Premier League for the full sample from season 2005/06 until 2018/19. We then fit our model to season-by-season data to investigate whether biases are of temporary nature only. To analyse whether inefficiencies exist within seasons, we additionally control for the round (i.e. the number of the current matchday). After discussing results for England in detail, a brief summary on analogue results obtained for the other four European top leagues is provided. We then analyse the profitability of betting strategies that result from the identified biases. Finally, we run a simulation experiment to put the number of significant results into perspective with what would be expected in an efficient market.

Modelling betting market inefficiencies

To detect betting market inefficiencies, we use a logistic regression model where the response variable $Won_i \in \{0, 1\}$ indicates whether bet i won. This enables the analysis of the explanatory power of covariates on the winning probability of a bet beyond the odds of bookmakers, thus investigating the efficient market hypothesis. Our analysis follows the typical approach of many previous studies on betting market inefficiencies (see, e.g., Forrest and Simmons, 2008; Franck et al., 2011; Feddersen et al., 2017).

The *Implied probability* provides information on a possible favourite-longshot bias. Specifically, it enables a comparison between the implied probability given by the bookmaker and the expected winning probability under our fitted model to reveal a potential *favourite-longshot bias*. To distinguish between the biases introduced in the literature overview, we further include a dummy variable indicating bets on home teams (*Home*) to account for a potential home bias. Bettors' sentiment is proxied by the covariate *DiffAttend*. *Model 1* includes these two covariates as well as the probability of the outcome as implied by the betting odds. As recent studies revealed evidence for the existence of market inefficiencies when betting on promoted teams, *Model 2* additionally accounts for these potential biases. It allows for different effects of promoted teams playing at home or away, captured by the four dummy variables *OnPromotedHome, OnPromotedAway, AgainstPromotedHome,* and *AgainstPromotedAway.* Table 4 provides an overview on the structure of the design matrix for our analyses.

As previous studies revealed that biases regarding promoted teams are likely to diminish during the season (see, e.g., Deutscher et al., 2018), *Model 3* includes the round, and *interactions* between *Round* and the effect of betting on (against) promoted teams. The linear predictor including all covariates introduced above (i.e. *Model 3*) is thus given by

$$
\begin{aligned}
\eta_i = \beta_0 &+ \beta_1 \mathit{ImpliedProbability}_i + \beta_2 \mathit{Home}_i + \beta_3 \mathit{DiffAttend}_i \\
&+ \beta_4 \mathit{AgainstPromotedHome}_i + \beta_5 \mathit{AgainstPromotedAway}_i \\
&+ \beta_6 \mathit{OnPromotedHome}_i + \beta_7 \mathit{OnPromotedAway}_i \\
&+ \beta_8 \mathit{Round}_i + \beta_9 \mathit{Round}_i \cdot \mathit{AgainstPromotedHome}_i \\
&+ \beta_{10} \mathit{Round}_i \cdot \mathit{AgainstPromotedAway}_i + \beta_{11} \mathit{Round}_i \cdot \mathit{OnPromotedHome}_i \\
&+ \beta_{12} \mathit{Round}_i \cdot \mathit{OnPromotedAway}_i.
\end{aligned}
$$

The logit function links the binary response variable Won_i to the linear predictor, i.e. $\text{logit}(\Pr(Won_i = 1)) = \eta_i$. The models are fitted by maximum likelihood using the function `glm()` in R, thus ensuring correct standard errors (R Core Team, 2019).

Table 4: Overview of the design matrix.

Home team	Away team	Season	Home	OnPromHome	OnPromAway	AgPromHome	AgPromAway	ImpProb	DiffAttend	HomeWin	AwayWin	Won	...
⋮	⋮		⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Newcastle	Chelsea	2005/06	1	0	0	0	0	0.323	10.13	1	0	1	...
Sunderland	Arsenal	2005/06	1	1	0	0	0	0.094	-4.280	0	1	0	...
Portsmouth	Liverpool	2005/06	0	0	0	0	0	0.571	24.40	0	1	1	...
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	...
Crystal Palace	Man City	2017/18	1	0	0	0	0	0.086	-28.75	0	0	0	...
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	...
Tottenham	Fulham	2018/19	1	0	0	1	0	0.749	29.85	1	0	1	...
Bournemouth	Cardiff	2018/19	0	0	1	0	0	0.219	20.88	1	0	0	...
Fulham	Crystal Palace	2018/19	0	0	0	0	1	0.327	1.084	0	1	1	...
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	...

Biases in the English Premier League

Table 5 displays the results of *Model 1* – *Model 3* fitted to the English Premier League. Our results suggest that game outcome is predicted strongly by the implied probability calculated from betting odds. According to *Model 1*, an increase of one percentage point in the *Implied probability* — all other covariates held constant — increases the odds of winning a bet by $\exp(\frac{5.004}{100}) = 1.051$. Perhaps somewhat surprisingly, we detect a *home* bias in all models. Therefore, betting on home teams increases the chances of winning a bet when controlling for the *Implied probability* and *DiffAttend*. Figure 3 displays the relationship between the probability implied by the bookmaker on the x-axis and the expected winning probability given by *Model 1* on the y-axis for home (right panel) and away games (left panel) including corresponding confidence intervals.

The dashed line corresponds to full efficiency, i.e. the implied probability equals the probability under the model since further effects beyond the home effect do not have any explanatory power. These results suggest bookmakers to undervalue favourites with implied probability between 0.5 and 0.8 in home games, whereas in away games underdogs with implied probability between 0.2 and 0.4 are overvalued. This favourite-longshot bias in the Premier League is in line with the findings by Direr (2011) and Franke (2020).

Model 2 implies that the home bias is to some extent driven by bets on home teams playing against promoted teams since we find a positive and significant effect for the dummy variable *AgainstPromotedHome* while the estimated effect of *Home* decreases. As we already control for the home bias, *AgainstPromotedHome* captures the

Table 5: Estimation results for *Model 1* – *Model 3* fitted to all seasons of the English Premier League.

	Response variable:		
	Won		
	Model 1	*Model 2*	*Model 3*
Implied probability	5.004***	4.964***	4.969***
	(0.181)	(0.188)	(0.188)
Home	0.136***	0.111*	0.110*
	(0.051)	(0.058)	(0.058)
DiffAttend	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)
AgainstPromotedHome		0.160*	0.021
		(0.091)	(0.178)
AgainstPromotedAway		0.004	−0.015
		(0.091)	(0.176)
OnPromotedHome		0.044	0.008
		(0.092)	(0.179)
OnPromotedAway		−0.022	0.244
		(0.110)	(0.211)
Round			0.002
			(0.002)
Round · AgainstPromotedHome			0.007
			(0.008)
Round · AgainstPromotedAway			0.001
			(0.008)
Round · OnPromotedHome			0.002
			(0.008)
Round · OnPromotedAway			−0.014
			(0.010)
Constant	−2.529***	−2.514***	−2.545***
	(0.066)	(0.071)	(0.085)
Observations	10,640	10,640	10,640
Note:	*p<0.1; **p<0.05; ***p<0.01		

additional effect of betting on home teams against promoted teams.[2] The interaction between round and the participation of promoted teams in *Model 3* reveals a positive but insignificant effect at the very beginning of the season. Since *Model 2* discloses a significant effect over the full season, our results challenge prior findings that inefficiencies regarding the evaluation of promoted teams occur primarily at the very beginning of the seasons (Deutscher et al., 2018).

To investigate whether biases are present for single seasons only, we fit *Model 3* to individual seasons. Each individual season contains 760 observations (380 matches per season · 2 rows for each match) with 102 bets on and against promoted teams, respectively. Table 6 displays the results for the English Premier League from season 2005/06 (first column) to season 2018/19 (last column).

Our results confirm the strong explanatory power of *Implied probabilities*, as this effect is statistically significant in all seasons considered. Meanwhile, all other esti-

[2]Teams playing against promoted teams at home often have larger implied winning probabilities (correlation 0.290, see Table 3).

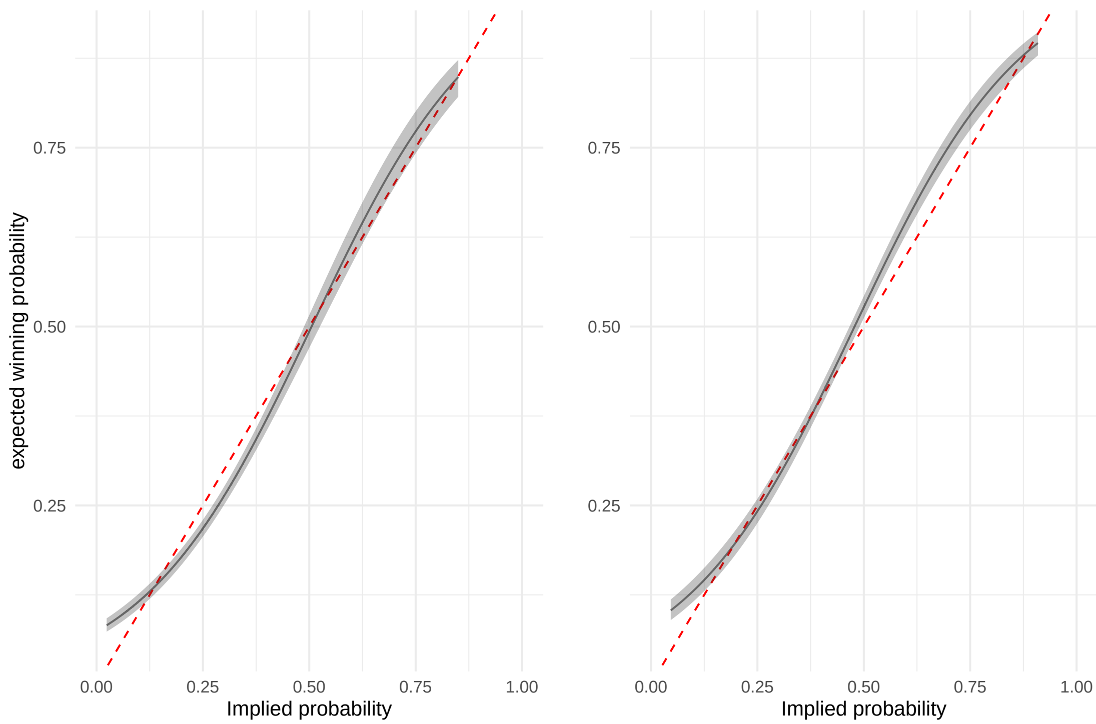

Figure 3: Probabilities for winning a bet under *Model 1* for away matches (left panel) and home matches (right panel). The covariate *DiffAttend* is set to its mean, i.e. zero, in this figure.

mated effects are significant in only some of the seasons. We find the same pattern as in Figure 3, i.e. higher expected winning probabilities for home teams with implied probabilities between 0.5 and 0.8, and lower expected winning probabilities for away teams with implied probabilities between 0.2 and 0.4, for four of the 14 seasons considered. This holds especially for seasons until 2010/11.[3] The findings provide evidence for the favourite-longshot bias for the English Premier League, although the results over the entire period considered are mainly driven by a small number of seasons. In addition, the existence of the home bias in the full sample in Table 5 is also determined by the positive effects in the seasons before 2010/11. After season 2010/11, the effect fluctuates around zero and remains statistically insignificant.

When evaluating the covariate *DiffAttend* as a proxy for the sentiment bias, three consecutive seasons (2009/10 until 2011/12) show that a higher average attendance positively affects the chances to win a bet. This suggests the temporary existence of

[3]Figures showing the expected winning probability for each season are presented upon request.

Table 6: Estimation results for *Model 3* fitted to individual seasons of the English Premier League.

	Response variable: Won													
	2005/06	2006/07	2007/08	2008/09	2009/10	2010/11	2011/12	2012/13	2013/14	2014/15	2015/16	2016/17	2017/18	2018/19
Implied probability	6.165***	4.964***	6.158***	5.347***	4.142***	2.837***	2.845***	5.122***	5.506***	5.026***	4.290***	5.989***	4.692***	5.155***
	(0.777)	(0.810)	(0.889)	(0.813)	(0.835)	(0.826)	(0.760)	(0.797)	(0.655)	(0.678)	(0.647)	(0.662)	(0.688)	(0.582)
Home	0.469**	0.144	−0.159	−0.151	0.779***	0.922***	0.066	−0.173	−0.254	−0.071	0.033	0.059	0.229	0.076
	(0.222)	(0.224)	(0.238)	(0.226)	(0.234)	(0.236)	(0.226)	(0.232)	(0.212)	(0.210)	(0.207)	(0.212)	(0.215)	(0.210)
DiffAttend	0.00001	0.002	0.002	0.006	0.013*	0.012*	0.021***	0.008	−0.001	−0.003	−0.006	−0.004	0.002	0.005
	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
AgPromHo.	−0.881	0.440	0.702	−0.673	−0.558	−0.437	−0.541	0.925	0.967	1.787**	−0.592	−0.500	0.142	0.081
	(0.675)	(0.668)	(0.783)	(0.644)	(0.668)	(0.623)	(0.643)	(0.705)	(0.734)	(0.772)	(0.653)	(0.720)	(0.656)	(0.687)
AgPromAw.	0.948	−1.221*	0.192	−0.261	−0.233	0.911	−0.795	−0.120	−0.335	0.094	0.455	−0.103	−0.192	0.266
	(0.638)	(0.720)	(0.674)	(0.655)	(0.697)	(0.696)	(0.703)	(0.676)	(0.664)	(0.641)	(0.636)	(0.643)	(0.683)	(0.662)
OnPromHo.	−0.254	0.199	0.127	0.873	0.238	−0.505	−0.671	0.121	0.925	−0.524	−0.576	0.970	−0.465	−0.583
	(0.676)	(0.665)	(0.714)	(0.640)	(0.638)	(0.719)	(0.680)	(0.674)	(0.661)	(0.756)	(0.690)	(0.635)	(0.731)	(0.687)
OnPromAw.	1.849***	−0.400	−2.303	1.024	0.375	1.828***	0.205	−0.200	−0.394	−1.068	0.503	0.123	0.718	−0.956
	(0.699)	(0.864)	(1.667)	(0.826)	(0.802)	(0.673)	(0.736)	(0.908)	(0.918)	(1.013)	(0.666)	(1.061)	(0.747)	(0.885)
Round	0.005	−0.006	−0.003	−0.0001	−0.009	0.012	−0.006	0.009	0.010	0.013	−0.006	0.003	−0.0002	−0.004
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Round · AgPromHo.	0.016	−0.010	0.016	0.038	0.033	0.006	0.034	−0.031	−0.033	−0.066**	0.054*	0.042	−0.009	−0.0002
	(0.030)	(0.030)	(0.035)	(0.029)	(0.030)	(0.028)	(0.029)	(0.031)	(0.030)	(0.032)	(0.030)	(0.034)	(0.029)	(0.030)
Round · AgPromAw.	−0.010	0.043	−0.003	0.005	−0.003	−0.025	0.003	−0.018	0.004	−0.003	0.013	−0.002	0.008	0.004
	(0.029)	(0.031)	(0.029)	(0.029)	(0.031)	(0.030)	(0.031)	(0.031)	(0.030)	(0.028)	(0.028)	(0.029)	(0.030)	(0.030)
Round · OnPromHo.	−0.009	0.001	0.002	−0.018	−0.026	0.004	0.053*	−0.003	−0.028	0.014	0.006	−0.026	0.030	0.033
	(0.031)	(0.029)	(0.031)	(0.028)	(0.031)	(0.031)	(0.029)	(0.030)	(0.030)	(0.032)	(0.030)	(0.029)	(0.031)	(0.031)
Round · OnPromAw.	−0.053	0.008	0.062	−0.103*	−0.007	−0.065*	−0.012	−0.009	−0.003	0.035	−0.009	−0.071	−0.034	0.051
	(0.033)	(0.038)	(0.060)	(0.057)	(0.036)	(0.034)	(0.034)	(0.041)	(0.037)	(0.039)	(0.030)	(0.063)	(0.036)	(0.036)
Constant	−3.138***	−2.403***	−2.857***	−2.522***	−2.410***	−2.464***	−1.546***	−2.681***	−2.635***	−2.674***	−2.205***	−2.914***	−2.537***	−2.417***
	(0.339)	(0.333)	(0.352)	(0.335)	(0.346)	(0.344)	(0.311)	(0.340)	(0.309)	(0.319)	(0.299)	(0.318)	(0.327)	(0.297)
Observations	760	760	760	760	760	760	760	760	760	760	760	760	760	760
Note:														*p<0.1; **p<0.05; ***p<0.01

a sentiment bias in the English Premier League. Considering matches with promoted teams involved, we find significantly higher chances to win a bet when betting against promoted teams in away games in season 2006/07, on promoted teams in away games in seasons 2005/06 and 2010/11, and when betting against promoted teams in home games in season 2014/15. The corresponding interaction effects indicate significant adjustments during the course of the season by bookmakers at least for the two latter cases (*OnPromotedAway* in 2010/11 and *AgainstPromotedHome* in 2014/15). In most cases, inefficiencies in matches with promoted teams are thus particularly limited to the very beginning of single seasons. Concluding, we do not find any systematic biases over time.

Further Leagues

The results on the biases analysed for further European top leagues can be obtained from the Appendix (see Tables 9 – 16) and are only briefly mentioned here. For all leagues considered, the models fitted to data of all seasons indicate a significant favourite-longshot bias for England, Italy, France, and Spain.[4] These results extend the findings of Forrest and Simmons (2008) who provide evidence for the existence of the favourite-longshot bias in the Spanish top division to further leagues. As also revealed by Forrest and Simmons (2008), our results suggest a sentiment bias which is limited to Spain according to our results (see Tables 9, 11, 13, and 15).

We find a significant home bias for the La Liga and the Bundesliga. While this bias occurs in all models for Spain, for the German Bundesliga, we find the home bias only in *Models 2* and *3*, where we allow for individual effects for matches containing promoted teams. Taking into account significantly increased chances to win a bet for away teams in these matches the home effect holds only for matches without promoted teams.[5] Considering interactions with the round underlines the results of Deutscher et al. (2018), revealing significantly increased chances betting on recently promoted teams in their away games at the very beginning of the season in Germany. In the model with interactions, the effect of betting against promoted teams in away games is not significant. The same result holds for the Italian Serie A. Furthermore, in the Spanish league we find a significantly positive effect for *AgainstPromotedAway* and significantly negative effect for *OnPromotedHome*, while in both cases significant adjustments during the course of the season do not occur. This implies that inefficiencies regarding recently promoted teams are not always limited to the very beginning of seasons.

Analysing single seasons, we find that the effects revealed over the full sample are mostly driven by a small number of individual seasons. For example, the sentiment and home biases in the Spanish La Liga are confined to only a few season where we find significant positive effects. Significantly higher chances to win when betting on recently promoted teams, at the very beginning of the season in the German Bundesliga, also occur in only three of the 14 seasons considered.

Returns

The estimated coefficients for the home effect, the sentiment bias, and for betting on/against promoted teams indicate that — at least for a few seasons — the chances of winning a bet are increased when following these strategies. We thus investigate

[4] Detailed figures are again shown upon request.

[5] We find positive significant effects for *OnPromotedAway* and *AgainstPromotedAway* in *Model 2*.

the profits generated by these strategies. Table 7 presents the ROI for all leagues and seasons, and the last column refers to the ROIs over the entire period. For *DiffAttend*, bets are placed on teams where the variable *DiffAttend* exceeds the 95% quantile of the corresponding league and season.[6]

Table 7: Returns on presented strategies for all leagues and seasons.

country	bet	2005/06	2006/07	2007/08	2008/09	2009/10	2010/11	2011/12	2012/13	2013/14	2014/15	2015/16	2016/17	2017/18	2018/19	all
England	*Home*	**0.036**	**0.008**	-0.094	-0.062	**0.084**	**0.002**	-0.043	-0.124	-0.007	-0.035	-0.104	**0.054**	**0.010**	**0.031**	-0.017
France	*Home*	-0.119	**0.004**	-0.087	-0.111	-0.021	-0.139	-0.016	-0.062	-0.114	**0.016**	-0.110	**0.049**	-0.062	-0.081	-0.061
Germany	*Home*	-0.204	-0.091	-0.042	0	-0.166	**0.015**	-0.042	-0.151	-0.006	**0.043**	-0.044	**0.100**	-0.018	-0.048	-0.047
Italy	*Home*	-0.106	-0.122	-0.055	**0.016**	-0.010	-0.020	-0.047	-0.059	-0.043	-0.137	-0.043	-0.004	-0.176	-0.082	-0.063
Spain	*Home*	-0.161	-0.067	-0.017	-0.034	**0.001**	**0.013**	**0.014**	**0.023**	**0.025**	-0.119	-0.003	-0.038	-0.027	-0.053	-0.032
England	*DiffAttend*	**0.012**	**0.117**	-0.011	**0.249**	**0.012**	-0.161	**0.080**	**0.143**	**0.017**	-0.11	**0.072**	-0.024	-0.098	**0.129**	**0.026**
France	*DiffAttend*	-0.172	-0.038	-0.168	**0.127**	-0.066	-0.093	-0.180	-0.087	**0.003**	-0.055	-0.152	**0.018**	-0.166	**0.159**	-0.016
Germany	*DiffAttend*	-0.105	-0.056	-0.038	**0.091**	**0.083**	**0.217**	**0.055**	**0.201**	-0.154	-0.163	**0.107**	-0.135	-0.145	**0.069**	**0.005**
Italy	*DiffAttend*	**0.070**	-0.126	-0.149	-0.022	**0.173**	**0.046**	**0.218**	**0.183**	-0.084	-0.051	**0.012**	**0.208**	-0.005	-0.043	**0.040**
Spain	*DiffAttend*	**0.003**	-0.076	-0.074	-0.067	**0.158**	-0.111	-0.054	**0.024**	-0.056	**0.046**	-0.012	-0.090	-0.03	-0.078	-0.028
England	*AgPromHo.*	-0.091	**0.045**	**0.280**	**0.019**	**0.093**	-0.132	**0.005**	**0.014**	**0.062**	**0.116**	-0.020	**0.142**	-0.055	**0.131**	**0.044**
France	*AgPromHo.*	-0.171	-0.029	-0.021	**0.050**	-0.204	-0.077	-0.274	**0.008**	-0.215	-0.008	**0.091**	-0.031	**0.052**	-0.198	-0.071
Germany	*AgPromHo.*	-0.007	-0.162	**0.006**	-0.103	-0.154	-0.061	-0.274	-0.106	-0.050	-0.002	-0.377	-0.158	**0.061**	-0.017	-0.098
Italy	*AgPromHo.*	-0.183	**0.018**	-0.013	-0.161	-0.014	**0.005**	-0.002	-0.100	-0.014	-0.163	-0.132	**0.123**	**0.076**	-0.053	-0.044
Spain	*AgPromHo.*	-0.118	-0.144	-0.006	**0.018**	**0.042**	**0.183**	**0.216**	**0.151**	**0.109**	-0.144	-0.147	-0.064	-0.320	-0.061	-0.020
England	*AgPromAw.*	**0.193**	-0.357	-0.101	-0.125	-0.326	-0.099	-0.318	-0.205	-0.112	-0.088	**0.223**	-0.020	-0.142	**0.204**	-0.091
France	*AgPromAw.*	-0.309	-0.246	**0.126**	**0.103**	-0.353	-0.138	**0.028**	-0.266	-0.056	**0.349**	-0.118	-0.041	-0.101	-0.355	-0.093
Germany	*AgPromAw.*	-0.039	**0.112**	**0.150**	-0.033	-0.074	**0.151**	**0.188**	**0.157**	**0.231**	-0.200	-0.101	-0.272	-0.318	**0.027**	**0.005**
Italy	*AgPromAw.*	-0.014	-0.228	-0.140	**0.193**	-0.097	**0.046**	-0.292	**0.240**	**0.132**	-0.123	**0.144**	-0.077	**0.054**	-0.024	-0.013
Spain	*AgPromAw.*	**0.050**	**0.017**	-0.180	-0.036	-0.194	-0.145	-0.137	-0.037	-0.158	**0.267**	0	-0.123	-0.022	-0.010	-0.050
England	*OnPromHo.*	-0.289	-0.040	-0.293	**0.108**	**0.015**	-0.174	**0.255**	-0.126	**0.151**	-0.188	-0.362	**0.314**	**0.196**	-0.075	-0.036
France	*OnPromHo.*	-0.261	-0.255	-0.157	-0.204	-0.014	-0.347	-0.017	**0.115**	-0.128	-0.288	-0.342	-0.158	**0.268**	**0.312**	-0.114
Germany	*OnPromHo.*	-0.506	-0.004	-0.301	-0.124	-0.039	-0.284	-0.284	-0.405	-0.072	-0.240	-0.434	**0.513**	**0.520**	-0.002	-0.135
Italy	*OnPromHo.*	-0.132	-0.034	**0.153**	-0.533	**0.111**	**0.046**	**0.116**	-0.192	-0.189	-0.200	-0.213	-0.063	-0.245	-0.276	-0.118
Spain	*OnPromHo.*	-0.171	-0.183	-0.044	-0.028	-0.163	**0.183**	-0.042	-0.317	-0.058	-0.514	-0.019	-0.441	**0.361**	-0.219	-0.118
England	*OnPromAw.*	**0.108**	-0.458	-0.674	-0.307	-0.239	**0.557**	-0.036	-0.459	-0.304	-0.350	**0.099**	-0.749	-0.279	**0.053**	-0.217
France	*OnPromAw.*	**0.116**	**0.165**	-0.566	-0.303	-0.019	-0.065	-0.143	-0.454	-0.069	-0.246	-0.022	-0.338	-0.347	**0.005**	-0.167
Germany	*OnPromAw.*	-0.235	**0.112**	**0.451**	**0.286**	**0.029**	**0.441**	-0.201	-0.101	-0.162	-0.007	**0.503**	**0.024**	**0.184**	-0.512	**0.063**
Italy	*OnPromAw.*	-0.573	-0.265	-0.052	**0.156**	-0.070	-0.251	-0.307	-0.142	-0.266	-0.313	-0.093	-0.502	-0.378	**0.207**	-0.204
Spain	*OnPromAw.*	**0.227**	**0.303**	-0.274	**0.279**	-0.509	**0.166**	**0.008**	-0.401	**0.026**	-0.274	-0.077	**0.428**	**0.081**	-0.285	-0.021

In seven of 14 seasons considered, positive returns are generated when betting on home teams in the English Premier League. However, over the full time period we do not find any league with positive returns when consistently betting on the home team. This appears somewhat surprisingly since we find a significant effect of the covariate *Home* in the regression models for England, Germany, and Spain (see Table 5, and Tables 11 and 15 in the Appendix). However, the related returns are not large enough to offset the average bookmaker margins of about 7%.

For teams with higher average attendance, we find positive returns in at least half of the seasons for the English, Italian, and German leagues, leading to positive returns over the entire period of 14 seasons. For a few seasons, the returns are fairly large (above 20% in England 2008/09, Germany in 2010/11 and 2012/13, as well as Italy 2011/12 and 2016/17). Total returns over all seasons are also positive, and account for up to 4%. These results are in line with previous findings on a positive sentiment bias in the Premier League (see Franck et al., 2011) and in the Primera Division (see Forrest and Simmons, 2008).

[6]For all strategies, we bet the same amount of money.

The different strategies for betting on games with promoted teams occasionally result in positive returns. Betting on promoted teams in away matches can generate high returns (above 50% in England 2010/11 and Germany 2015/16), and even leads to a total return of 6.3% over the entire period in Germany. However, applying this betting strategy in other countries yields substantial negative returns (France -16.7%, Italy -20.4%, and England -21.7%). Other profitable betting strategies include betting against promoted teams in their away games (total return of 4.4% in England, and positive returns in eleven of 14 seasons considered), and betting against promoted teams in their home games (return of 0.5% in Germany). Still, there is a high variance in the latter strategy, as returns in Germany vary between 15% and -31.8% during the period observed. These findings confirm the results of Deutscher et al. (2018), who find that promoted teams are hard to evaluate for bookmakers, especially in the German Bundesliga. However, we do not find any promising systematic strategy over all leagues and seasons.

Concluding, we find several leagues and seasons where positive returns can be generated in the short run. However, in the long run, there are only a few profitable betting strategies, mostly driven by the sentiment bias and the promoted team bias. In addition, returns are highly volatile and differ between seasons. The fairly high positive returns for single seasons shown here illustrate the possibility to find betting strategies with positive returns in the short run (as presented in the existing literature, see Table 1). Nevertheless, in the long run we find only very few betting strategies which generate positive returns, even in more recent seasons with lower bookmaker margins. This suggests that our findings are unsystematic and at least to some extent driven by statistical noise.

Simulations for the case of full market efficiency

To examine whether the biases in betting markets studied above could be observed by chance only, we conduct a simulation experiment. Our simulation is based on the data set for the English Premier League presented in the previous section and contains fourteen seasons. Fully efficient markets would imply that the probability of a match outcome is completely given by the bookmakers' odds. Therefore, we use Monte

Carlo techniques to simulate $n = 10,000$ realisations of results (home win, draw, away win) for each match according to the underlying implied probability suggested by the bookmakers' odds for 5,320 matches between seasons 2005/06 and 2018/19. In each simulation run we fit Model 1 to the data. Analogue to the previous section, we then test for the home and sentiment bias, respectively, analysing single seasons as well as the whole time horizon. Finally, we also present the corresponding ROIs for these two potential biases.

Table 8: Results obtained in our simulation: the t-th row shows the proportion of simulation runs where we find at least t seasons with a statistically significant bias for $p = 0.1$, $p = 0.05$, and $p = 0.01$.

		Home			*DiffAttend*	
#Seasons	p=0.1	p=0.05	p=0.01	p=0.1	p=0.05	p=0.01
1	78.04%	61.34%	27.32%	98.81%	97.88%	96.00%
2	45.17%	24.69%	4.09%	92.58%	88.03%	81.11%
3	18.83%	7.13%	0.41%	77.41%	69.06%	56.87%
4	6.08%	1.47%	0.02%	54.75%	44.25%	31.65%
5	1.67%	0.33%	0.01%	31.78%	22.95%	13.91%
6	0.41%	0.06%	0.01%	15.66%	10.06%	5.18%
7	0.06%	0.01%	0	6.31%	3.32%	1.40%
8	0	0	0	1.65%	0.85%	0.27%
9	0	0	0	0.40%	0.14%	0.05%
10	0	0	0	0.05%	0.01%	0.01%
11	0	0	0	0.01%	0.01%	0.01%
12	0	0	0	0.01%	0.01%	0
13	0	0	0	0	0	0
14	0	0	0	0	0	0
Full period	14.75%	9.72%	3.59%	18.69%	12.76%	5.35%

Table 8 displays the results of the simulation. Specifically, the t-th row shows the proportion of simulation runs where we find at least t seasons with a statistically significant bias (for $p = 0.1$, $p = 0.05$, and $p = 0.01$). Even when assuming fully efficient markets, in 78.04% of our simulation runs we find at least one season with a significant home bias on the 10% significance level. Moreover, at least one positive significant effect of *DiffAttend* can be found in nearly every simulation run. Even over the full observation period we find a positive significant home effect in 14.75% and a positive effect for the difference in the average attendance in 18.69% of the simulation runs. These results clearly indicate that the occurrence of significant effects in the previous section does not necessarily result from biases, but can also be observed under full market efficiency due to statistical noise.

Therefore, we further consider the ROIs obtained in our simulation. While we occasionally observe fairly high returns for single seasons when consistently betting on the home team, Figure 4 shows boxplots of the average returns when always betting on the home team in all fourteen seasons. The average return is close to the negative average margin in the English Premier League, which is obtained as about 6.2% over all fourteen seasons analysed.

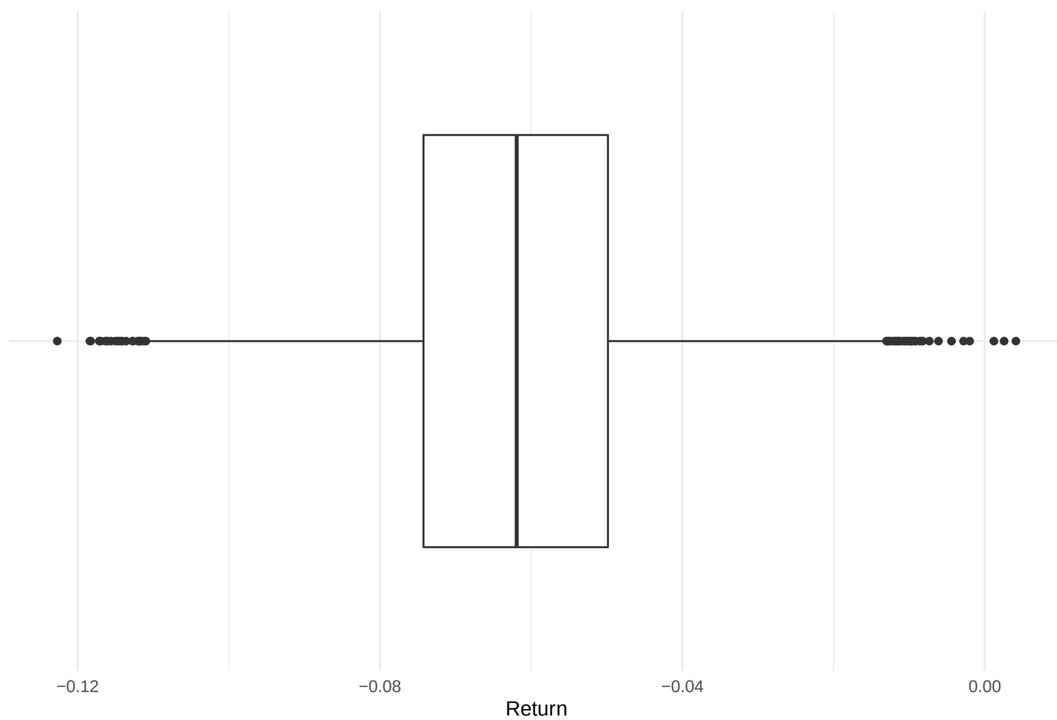

Figure 4: Boxplot on the average ROI over all matches when consistently betting on the home team in the simulation runs.

In our real-data analysis of the English Premier League, we obtained a significant effect for the home and the sentiment bias in three of fourteen seasons considered (see Table 6). Comparing these results to our findings from the simulation experiment, we see that under fully efficient markets, the sentiment bias is observed in at least three of fourteen seasons with an estimated probability of 77.41%, while we observe a home bias in at least three seasons with an estimated probability of 18.83%. This indicates that the biases found in our data are not necessarily driven by market inefficiencies but might also be the result of statistical noise.

5 Discussion

While efficient markets should incorporate all available information, previous literature revealed promising strategies for bettors in European football. Due to increased competition and reduced margins, bookmakers had to further improve their forecast precision to remain profitable. In the light of this major changes of betting markets and the narrow time period of data covered by most previous studies, the question whether inefficiencies are of a temporary nature only or persist over time arises. We further put the number of statistically significant results into perspective by performing Monte Carlo simulations on the actual betting data.

Our results indicate different temporal biases in the betting market for premier European football. However, those biases typically vanish fast while they appear and disappear unsystematic for only a few leagues. Furthermore, any long-term results are mostly driven by a singular seasons with particular large returns. The possibility of generating positive returns using certain strategies for short periods is not necessarily a result of biases in the bookmakers' odds but can also be observed due to statistical noise. This is underlined by our simulation experiment which reveals an estimated probability of about 25% to generate positive returns for single seasons even in fully efficient markets. In such season-by-season analysis, a limited number of significant results is expected even in this setting due to the type I error of hypothesis testing. Considering the wide discussion on p-hacking in empirical studies (see, e.g., Head et al., 2015), future research should cover a sufficient number of observations when analysing inefficiencies in betting markets to uncover long-term biases which are less likely to be caused by chance and statistical noise only.

Betting market research has been and will be of major interest due to the economic impact it has and the entanglement with the sport itself. Potentially both, bettors and bookmakers profit from increasing real-time information as valuable source in price setting. The lack of such information is given when sports face settings that have rarely, if at all, occurred in the past. Next to leagues merging and cup competitions, a very recent example is the absence of spectators due to COVID-19. While the home advantage vanished in some leagues, bookmakers had difficulties to react to this systematic change (Deutscher et al., 2020; Fischer and Haucap, 2020). It remains to be seen if and how fast they can adept in this and other settings.

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6 Appendix

Table 9: Estimation results for *Model 1 – Model 3* fitted to all seasons of the French Ligue 1.

	Response variable:		
	Won		
	Model 1	Model 2	Model 3
Implied probability	5.101***	5.100***	5.104***
	(0.230)	(0.239)	(0.240)
Home	0.012	0.041	0.040
	(0.057)	(0.064)	(0.064)
DiffAttend	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)
AgainstPromotedHome		−0.095	−0.016
		(0.087)	(0.170)
AgainstPromotedAway		0.071	0.014
		(0.091)	(0.178)
OnPromotedHome		−0.045	0.107
		(0.091)	(0.178)
OnPromotedAway		−0.011	0.090
		(0.107)	(0.205)
Round			−0.0004
			(0.002)
Round · AgainstPromotedHome			−0.004
			(0.008)
Round · AgainstPromotedAway			0.003
			(0.008)
Round · OnPromotedHome			−0.008
			(0.008)
Round · OnPromotedAway			−0.005
			(0.009)
Constant	−2.497***	−2.506***	−2.499***
	(0.074)	(0.078)	(0.090)
Observations	10,640	10,640	10,640
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 10: Estimation results for *Model 1 – Model 3* fitted to all seasons of the French Ligue 1.

	Response variable:													
	Won													
	2005/06	2006/07	2007/08	2008/09	2009/10	2010/11	2011/12	2012/13	2013/14	2014/15	2015/16	2016/17	2017/18	2018/19
Implied probability	5.565***	2.339**	4.109***	4.543***	5.601***	4.802***	6.855***	3.904***	5.894***	4.732***	4.676***	6.104***	5.446***	3.742***
	(1.027)	(1.045)	(1.260)	(1.236)	(0.885)	(1.006)	(1.162)	(1.219)	(0.831)	(0.889)	(0.942)	(0.859)	(0.711)	(0.848)
Home	−0.036	0.913***	0.086	−0.068	−0.038	0.011	0.116	0.006	−0.087	0.315	−0.173	0.245	−0.197	0.131
	(0.269)	(0.270)	(0.294)	(0.295)	(0.237)	(0.259)	(0.269)	(0.281)	(0.237)	(0.230)	(0.234)	(0.223)	(0.223)	(0.222)
DiffAttend	0.005	0.006	−0.001	0.008	−0.007	−0.004	−0.011	0.012	0.004	0.003	−0.0003	−0.006	0.001	0.014**
	(0.006)	(0.006)	(0.006)	(0.008)	(0.007)	(0.007)	(0.010)	(0.011)	(0.007)	(0.007)	(0.007)	(0.008)	(0.006)	(0.007)
AgPromHo.	0.308	−0.206	0.423	0.439	−0.730	0.618	0.100	0.882	−0.315	−0.183	−0.180	−0.598	−0.192	−0.831
	(0.639)	(0.608)	(0.624)	(0.606)	(0.639)	(0.622)	(0.657)	(0.672)	(0.669)	(0.599)	(0.683)	(0.659)	(0.648)	(0.744)
AgPromAw.	−0.526	−0.069	−0.240	0.516	−0.339	0.163	0.889	0.520	−0.289	0.646	−0.733	0.283	−0.192	−0.443
	(0.695)	(0.678)	(0.644)	(0.646)	(0.676)	(0.682)	(0.663)	(0.656)	(0.741)	(0.651)	(0.707)	(0.643)	(0.656)	(0.861)
OnPromHo.	0.518	−0.223	−0.115	0.396	0.172	−0.250	1.048	−0.087	0.897	−0.609	−1.115	0.117	0.340	−0.428
	(0.642)	(0.641)	(0.649)	(0.672)	(0.644)	(0.759)	(0.664)	(0.659)	(0.656)	(0.718)	(0.800)	(0.644)	(0.664)	(0.831)
OnPromAw.	0.592	−0.648	−0.221	0.259	0.040	0.299	−0.929	−2.214*	0.062	0.562	1.044	0.474	0.260	0.916
	(0.713)	(0.820)	(0.878)	(0.759)	(0.709)	(0.735)	(1.061)	(1.260)	(0.712)	(0.710)	(0.766)	(0.808)	(0.792)	(0.740)
Round	0.0004	−0.006	−0.004	0.004	−0.015*	0.001	0.019**	0.004	0.001	0.002	0.0003	−0.001	−0.008	−0.004
	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.008)
Round · AgPromHo.	−0.031	0.012	−0.011	−0.003	0.009	−0.027	−0.049*	−0.034	0.008	−0.0002	0.028	0.014	0.022	0.026
	(0.028)	(0.028)	(0.028)	(0.028)	(0.029)	(0.027)	(0.030)	(0.028)	(0.030)	(0.028)	(0.031)	(0.030)	(0.029)	(0.033)
Round · AgPromAw.	0.013	0.012	0.037	−0.003	−0.003	−0.001	−0.026	−0.048	0.020	0.010	0.032	−0.008	0.002	−0.008
	(0.030)	(0.030)	(0.029)	(0.028)	(0.031)	(0.029)	(0.028)	(0.031)	(0.032)	(0.028)	(0.031)	(0.029)	(0.029)	(0.038)
Round · OnPromHo.	−0.035	−0.020	−0.001	−0.023	−0.002	−0.003	−0.050*	0.021	−0.047	0.005	0.037	−0.018	0.004	0.047
	(0.030)	(0.030)	(0.030)	(0.030)	(0.028)	(0.032)	(0.029)	(0.028)	(0.030)	(0.031)	(0.034)	(0.029)	(0.030)	(0.036)
Round · OnPromAw.	−0.009	0.048	−0.034	−0.037	0.009	−0.013	0.053	0.073	0.008	−0.050	−0.066*	−0.037	−0.032	−0.031
	(0.031)	(0.034)	(0.046)	(0.040)	(0.031)	(0.034)	(0.040)	(0.045)	(0.031)	(0.040)	(0.040)	(0.041)	(0.041)	(0.035)
Constant	−2.638***	−1.858***	−2.098***	−2.374***	−2.259***	−2.524***	−3.553***	−2.135***	−2.814***	−2.447***	−2.241***	−2.873***	−2.394***	−2.045***
	(0.352)	(0.354)	(0.393)	(0.392)	(0.323)	(0.353)	(0.408)	(0.402)	(0.328)	(0.342)	(0.345)	(0.340)	(0.310)	(0.327)
Observations	760	760	760	760	760	760	760	760	760	760	760	760	760	760
Note:														*p<0.1; **p<0.05; ***p<0.01

Table 11: Estimation results for *Model 1 – Model 3* fitted to all seasons of the German Bundesliga.

	Response variable:		
	Won		
	Model 1	Model 2	Model 3
Implied probability	4.459***	4.476***	4.474***
	(0.195)	(0.201)	(0.201)
Home	0.069	0.152**	0.152**
	(0.055)	(0.062)	(0.062)
DiffAttend	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)
AgainstPromotedHome		−0.145	−0.067
		(0.100)	(0.195)
AgainstPromotedAway		0.209**	0.227
		(0.102)	(0.198)
OnPromotedHome		−0.121	0.216
		(0.104)	(0.202)
OnPromotedAway		0.204*	0.384*
		(0.114)	(0.221)
Round			0.004
			(0.003)
Round · AgainstPromotedHome			−0.004
			(0.010)
Round · AgainstPromotedAway			−0.001
			(0.010)
Round · OnPromotedHome			−0.020*
			(0.010)
Round · OnPromotedAway			−0.010
			(0.011)
Constant	−2.272***	−2.330***	−2.402***
	(0.071)	(0.076)	(0.091)
Observations	8,568	8,568	8,568
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 12: Estimation results for *Model 1 – Model 3* fitted to all seasons of the German Bundesliga.

	Response variable:													
	Won													
	2005/06	2006/07	2007/08	2008/09	2009/10	2010/11	2011/12	2012/13	2013/14	2014/15	2015/16	2016/17	2017/18	2018/19
Implied probability	5.998***	4.350***	4.394***	4.030***	4.396***	2.645***	4.096***	4.639***	5.835***	4.611***	4.390***	2.627***	5.068***	5.212***
	(1.064)	(0.950)	(0.934)	(0.761)	(0.695)	(0.767)	(0.854)	(0.868)	(0.770)	(0.673)	(0.694)	(0.738)	(0.766)	(0.692)
Home	−0.128	−0.060	0.410	0.474*	−0.303	0.301	0.275	−0.094	−0.009	0.560**	0.244	0.693***	−0.031	−0.074
	(0.282)	(0.262)	(0.256)	(0.246)	(0.237)	(0.222)	(0.237)	(0.248)	(0.226)	(0.217)	(0.219)	(0.228)	(0.229)	(0.222)
DiffAttend	0.003	−0.001	0.001	0.009**	0.005	0.004	0.007	0.006	−0.006	−0.009**	0.009*	0.013***	−0.0002	−0.001
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
AgPromHo.	1.434*	0.070	−0.413	0.816	0.185	0.596	−0.489	−0.480	−0.763	−0.401	−2.902***	−0.259	1.514*	−0.776
	(0.789)	(0.683)	(0.668)	(0.692)	(0.683)	(0.753)	(0.788)	(0.702)	(0.838)	(0.828)	(0.974)	(0.769)	(0.804)	(0.818)
AgPromAw.	0.417	0.950	0.911	0.381	0.269	−0.246	0.214	−0.802	0.807	0.605	−0.067	−1.544	−0.976	0.854
	(0.681)	(0.689)	(0.681)	(0.706)	(0.668)	(0.793)	(0.806)	(0.707)	(0.755)	(0.812)	(0.799)	(1.117)	(1.041)	(0.795)
OnPromHo.	0.502	0.123	0.372	1.135	0.178	−0.673	−1.226	0.489	0.299	−0.631	−0.824	2.477**	1.629*	−0.375
	(0.719)	(0.733)	(0.727)	(0.706)	(0.711)	(0.896)	(0.915)	(0.726)	(0.784)	(0.876)	(0.966)	(0.998)	(0.846)	(0.860)
OnPromAw.	−0.893	−0.046	1.548**	0.570	0.224	0.363	−0.394	0.748	0.302	1.789**	1.823**	0.633	−1.228	−1.130
	(1.088)	(0.842)	(0.706)	(0.744)	(0.800)	(0.764)	(1.038)	(0.758)	(0.999)	(0.882)	(0.825)	(0.786)	(1.123)	(1.346)
Round	0.006	0.022**	0.002	0.017	0.006	−0.002	−0.007	0.00001	0.006	0.011	−0.005	−0.001	0.009	−0.004
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)
Round · AgPromHo.	−0.074*	−0.008	0.025	−0.052	−0.016	−0.032	−0.008	0.019	0.031	0.020	0.091**	−0.019	−0.069*	0.043
	(0.039)	(0.032)	(0.033)	(0.034)	(0.035)	(0.037)	(0.040)	(0.034)	(0.041)	(0.041)	(0.045)	(0.040)	(0.040)	(0.040)
Round · AgPromAw.	−0.005	−0.034	−0.012	−0.007	−0.030	0.038	0.008	0.065*	−0.023	−0.025	−0.001	0.061	0.036	−0.050
	(0.033)	(0.034)	(0.034)	(0.034)	(0.033)	(0.040)	(0.039)	(0.036)	(0.039)	(0.039)	(0.040)	(0.049)	(0.048)	(0.042)
Round · OnPromHo.	−0.053	0.005	−0.048	−0.089**	0.001	−0.002	0.041	−0.059	−0.032	−0.001	0.024	−0.084*	−0.033	0.037
	(0.038)	(0.035)	(0.039)	(0.039)	(0.034)	(0.046)	(0.042)	(0.041)	(0.044)	(0.043)	(0.046)	(0.046)	(0.041)	(0.043)
Round · OnPromAw.	0.053	0.018	−0.060	−0.006	−0.015	0.004	0.004	−0.049	−0.037	−0.081*	−0.059	−0.005	0.075	0.038
	(0.050)	(0.037)	(0.038)	(0.035)	(0.042)	(0.038)	(0.054)	(0.040)	(0.052)	(0.049)	(0.044)	(0.040)	(0.050)	(0.058)
Constant	−3.028***	−2.585***	−2.510***	−2.607***	−2.208***	−1.548***	−2.090***	−2.257***	−2.790***	−2.827***	−2.184***	−1.917***	−2.750***	−2.450***
	(0.417)	(0.380)	(0.378)	(0.352)	(0.330)	(0.321)	(0.347)	(0.368)	(0.350)	(0.341)	(0.331)	(0.335)	(0.356)	(0.322)
Observations	612	612	612	612	612	612	612	612	612	612	612	612	612	612
Note:														*p<0.1; **p<0.05; ***p<0.01

Table 13: Estimation results for *Model 1 – Model 3* fitted to all seasons of the Italian Serie A.

	Response variable:		
	Won		
	Model 1	*Model 2*	*Model 3*
Implied probability	5.309^{***}	5.317^{***}	5.317^{***}
	(0.227)	(0.235)	(0.235)
Home	0.054	0.093	0.093
	(0.057)	(0.064)	(0.064)
DiffAttend	0.004^{*}	0.003^{*}	0.003^{*}
	(0.002)	(0.002)	(0.002)
AgainstPromotedHome		−0.147	−0.194
		(0.090)	(0.176)
AgainstPromotedAway		0.183^{**}	0.137
		(0.091)	(0.179)
OnPromotedHome		0.030	−0.080
		(0.093)	(0.183)
OnPromotedAway		−0.055	-0.418^{*}
		(0.114)	(0.238)
Round			−0.001
			(0.002)
Round · AgainstPromotedHome			0.002
			(0.008)
Round · AgainstPromotedAway			0.002
			(0.008)
Round · OnPromotedHome			0.006
			(0.008)
Round · OnPromotedAway			0.018^{*}
			(0.010)
Constant	-2.611^{***}	-2.638^{***}	-2.609^{***}
	(0.075)	(0.080)	(0.091)
Observations	10,640	10,640	10,640
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 14: Estimation results for *Model 1 – Model 3* fitted to all seasons of the Italian Serie A.

	Response variable:													
	Won													
	2005/06	2006/07	2007/08	2008/09	2009/10	2010/11	2011/12	2012/13	2013/14	2014/15	2015/16	2016/17	2017/18	2018/19
Implied probability	6.315^{***}	4.684^{***}	4.949^{***}	5.195^{***}	4.072^{***}	3.575^{***}	4.520^{***}	6.959^{***}	5.924^{***}	2.906^{***}	5.604^{***}	6.314^{***}	6.156^{***}	6.280^{***}
	(1.028)	(1.037)	(0.869)	(0.965)	(0.948)	(0.902)	(1.057)	(1.066)	(0.991)	(0.966)	(0.971)	(0.809)	(0.797)	(0.744)
Home	0.107	0.176	0.194	0.743^{***}	0.539^{**}	0.304	0.039	−0.184	0.114	0.085	0.162	−0.150	-0.622^{***}	0.197
	(0.264)	(0.280)	(0.246)	(0.252)	(0.256)	(0.249)	(0.263)	(0.259)	(0.250)	(0.241)	(0.240)	(0.227)	(0.228)	(0.218)
DiffAttend	0.006	0.018^{**}	0.004	0.001	0.018^{***}	0.014^{**}	0.001	−0.011	0.005	0.017^{*}	−0.001	−0.005	−0.001	−0.006
	(0.008)	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.007)	(0.006)
AgPromHo.	−0.642	−0.109	−1.088	−0.556	-1.248^{*}	0.886	−0.162	-1.201^{*}	−0.236	−0.200	0.485	0.833	0.549	0.057
	(0.655)	(0.664)	(0.737)	(0.655)	(0.640)	(0.687)	(0.611)	(0.690)	(0.688)	(0.648)	(0.703)	(0.767)	(0.762)	(0.683)
AgPromAw.	−0.186	0.439	0.602	0.765	−0.488	−0.090	−0.464	0.604	−0.039	−0.911	0.189	0.312	0.783	0.489
	(0.673)	(0.708)	(0.742)	(0.633)	(0.709)	(0.664)	(0.724)	(0.672)	(0.687)	(0.695)	(0.653)	(0.657)	(0.695)	(0.670)
OnPromHo.	−0.576	0.357	0.071	-1.381^{*}	−0.145	0.867	0.020	0.113	1.011	0.079	−0.007	−1.053	−0.601	−0.268
	(0.723)	(0.642)	(0.643)	(0.764)	(0.630)	(0.670)	(0.669)	(0.688)	(0.688)	(0.708)	(0.715)	(0.771)	(0.822)	(0.757)
OnPromAw.	−1.891	0.052	0.128	0.255	0.044	−1.313	−0.885	0.980	−0.825	−1.607	−0.021	−0.937	−1.874	1.063
	(1.354)	(0.841)	(0.740)	(0.797)	(0.834)	(1.081)	(0.884)	(0.899)	(1.002)	(1.118)	(0.842)	(1.033)	(1.353)	(0.744)
Round	−0.014	0.005	0.014	−0.007	−0.012	0.008	−0.006	−0.007	0.005	0.00001	0.001	−0.009	−0.003	0.002
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Round · AgPromHo.	0.001	0.020	0.049	−0.013	0.055^{*}	−0.045	0.018	0.038	0.004	0.004	−0.048	−0.031	−0.009	−0.013
	(0.030)	(0.029)	(0.031)	(0.029)	(0.030)	(0.030)	(0.028)	(0.031)	(0.029)	(0.027)	(0.029)	(0.033)	(0.034)	(0.029)
Round · AgPromAw.	0.020	−0.020	−0.031	0.003	0.032	0.009	0.013	0.001	0.023	0.042	0.006	−0.024	-0.051^{*}	−0.004
	(0.030)	(0.032)	(0.034)	(0.029)	(0.031)	(0.029)	(0.032)	(0.030)	(0.030)	(0.030)	(0.029)	(0.030)	(0.031)	(0.029)
Round · OnPromHo.	0.040	−0.010	0.005	0.009	0.025	−0.043	0.017	−0.006	−0.051	−0.010	−0.010	0.068^{**}	0.050	0.011
	(0.031)	(0.030)	(0.029)	(0.033)	(0.028)	(0.031)	(0.029)	(0.031)	(0.032)	(0.031)	(0.032)	(0.033)	(0.034)	(0.032)
Round · OnPromAw.	0.084	−0.003	−0.004	0.016	0.003	0.053	0.026	-0.107^{*}	0.048	0.048	0.018	0.025	0.050	−0.023
	(0.052)	(0.036)	(0.031)	(0.035)	(0.039)	(0.040)	(0.038)	(0.064)	(0.038)	(0.042)	(0.033)	(0.044)	(0.053)	(0.033)
Constant	-2.761^{***}	-2.654^{***}	-2.859^{***}	-2.692^{***}	-2.201^{***}	-2.204^{***}	-2.235^{***}	-2.903^{***}	-2.974^{***}	-1.798^{***}	-2.764^{***}	-2.663^{***}	-2.535^{***}	-3.262^{***}
	(0.369)	(0.362)	(0.341)	(0.353)	(0.342)	(0.330)	(0.365)	(0.373)	(0.375)	(0.354)	(0.364)	(0.329)	(0.340)	(0.353)
Observations	760	760	760	760	760	760	760	760	760	760	760	760	760	760
Note:														*p<0.1; **p<0.05; ***p<0.01

Table 15: Estimation results for *Model 1* – *Model 3* fitted to all seasons of the Spanish La Liga.

	Response variable:		
	Won		
	Model 1	*Model 2*	*Model 3*
Implied probability	4.623***	4.610***	4.602***
	(0.242)	(0.248)	(0.248)
Home	0.131**	0.170**	0.172***
	(0.060)	(0.066)	(0.066)
DiffAttend	0.004**	0.004**	0.004**
	(0.002)	(0.002)	(0.002)
AgainstPromotedHome		−0.021	−0.231
		(0.088)	(0.172)
AgainstPromotedAway		0.086	0.314*
		(0.091)	(0.176)
OnPromotedHome		−0.068	−0.299*
		(0.090)	(0.181)
OnPromotedAway		0.101	0.215
		(0.104)	(0.202)
Round			0.001
			(0.002)
Round · AgainstPromotedHome			0.011
			(0.008)
Round · AgainstPromotedAway			−0.012
			(0.008)
Round · OnPromotedHome			0.012
			(0.008)
Round · OnPromotedAway			−0.006
			(0.009)
Constant	−2.359***	−2.380***	−2.402***
	(0.078)	(0.083)	(0.094)
Observations	10,640	10,640	10,640
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 16: Estimation results for *Model 3* fitted to individual seasons of the Spanish La Liga.

	Response variable:													
	Won													
	2005/06	2006/07	2007/08	2008/09	2009/10	2010/11	2011/12	2012/13	2013/14	2014/15	2015/16	2016/17	2017/18	2018/19
Implied probability	5.309***	4.055***	4.264***	6.977***	4.288***	3.720***	3.797***	3.008***	3.471***	4.275***	5.426***	6.568***	4.291***	2.790***
	(1.157)	(1.156)	(1.039)	(1.148)	(0.986)	(1.101)	(1.019)	(1.086)	(0.947)	(0.923)	(0.978)	(0.875)	(0.785)	(1.008)
Home	−0.336	0.235	0.020	−0.234	0.711***	0.384	0.467*	0.475*	0.120	0.272	0.280	−0.001	0.204	0.428*
	(0.279)	(0.262)	(0.248)	(0.267)	(0.262)	(0.281)	(0.268)	(0.279)	(0.257)	(0.252)	(0.254)	(0.242)	(0.234)	(0.250)
DiffAttend	−0.0005	0.002	−0.0003	−0.003	0.013**	0.014*	0.008	0.016**	0.010	0.011	0.001	−0.007	0.009*	0.008
	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.006)	(0.005)	(0.006)
AgPromHo.	−0.255	−0.081	−0.218	0.115	0.992	−0.192	0.384	0.402	0.058	−0.684	−0.692	−1.094*	−1.742**	−0.353
	(0.627)	(0.633)	(0.624)	(0.672)	(0.756)	(0.671)	(0.660)	(0.670)	(0.645)	(0.664)	(0.666)	(0.660)	(0.709)	(0.634)
AgPromAw.	0.573	0.326	−0.779	0.017	1.294*	0.717	0.663	0.199	−0.280	−0.611	0.919	0.927	−0.815	1.250*
	(0.652)	(0.637)	(0.705)	(0.650)	(0.673)	(0.657)	(0.706)	(0.652)	(0.738)	(0.698)	(0.667)	(0.686)	(0.656)	(0.664)
OnPromHo.	0.002	−0.384	0.049	1.128*	−0.532	0.823	0.127	−0.216	−0.132	−0.613	−1.577**	−2.684**	−0.039	−1.831**
	(0.670)	(0.679)	(0.652)	(0.649)	(0.677)	(0.638)	(0.668)	(0.626)	(0.685)	(0.776)	(0.776)	(1.129)	(0.631)	(0.911)
OnPromAw.	0.758	0.252	−0.332	1.165*	−3.432*	0.357	0.635	−0.588	−0.169	0.938	0.623	1.379*	−1.524	0.702
	(0.664)	(0.735)	(0.802)	(0.690)	(1.931)	(0.797)	(0.732)	(0.846)	(0.707)	(0.784)	(0.738)	(0.706)	(0.944)	(0.780)
Round	0.002	0.001	0.004	0.011	−0.0001	0.004	0.009	−0.006	−0.006	−0.005	−0.001	0.004	−0.012	0.008
	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Round · AgPromHo.	0.017	−0.009	0.014	−0.007	−0.048	0.039	0.014	0.0001	0.016	0.016	0.012	0.037	0.043	0.026
	(0.028)	(0.028)	(0.027)	(0.030)	(0.032)	(0.034)	(0.030)	(0.030)	(0.028)	(0.029)	(0.029)	(0.031)	(0.030)	(0.029)
Round · AgPromAw.	−0.018	−0.002	0.016	0.002	−0.062*	−0.042	−0.023	−0.0003	−0.010	0.076**	−0.040	−0.055*	0.035	−0.047
	(0.028)	(0.028)	(0.030)	(0.028)	(0.033)	(0.030)	(0.031)	(0.029)	(0.033)	(0.033)	(0.031)	(0.033)	(0.030)	(0.030)
Round · OnPromHo.	0.013	0.005	−0.010	−0.046	0.016	−0.024	−0.0004	−0.010	0.003	−0.006	0.079**	0.099**	0.024	0.069*
	(0.028)	(0.030)	(0.029)	(0.029)	(0.029)	(0.027)	(0.030)	(0.029)	(0.030)	(0.037)	(0.033)	(0.043)	(0.028)	(0.036)
Round · OnPromAw.	−0.025	0.001	−0.012	−0.027	0.122*	−0.043	−0.019	0.012	0.018	−0.061	−0.007	−0.058	0.094**	−0.054
	(0.031)	(0.032)	(0.035)	(0.031)	(0.066)	(0.044)	(0.032)	(0.038)	(0.030)	(0.042)	(0.033)	(0.037)	(0.037)	(0.040)
Constant	−2.478***	−2.203***	−2.093***	−3.225***	−2.585***	−2.200***	−2.538***	−1.780***	−1.794***	−2.247***	−2.778***	−3.103***	−2.014***	−2.094***
	(0.388)	(0.394)	(0.366)	(0.407)	(0.368)	(0.392)	(0.382)	(0.382)	(0.348)	(0.359)	(0.372)	(0.355)	(0.320)	(0.377)
Observations	760	760	760	760	760	760	760	760	760	760	760	760	760	760
Note:														*p<0.1; **p<0.05; ***p<0.01