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Short and long-term biases in European football pre-game betting markets

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Abstract

Research on sports betting often attempts to identify biased evaluation by bookmakers, opening opportunities for profitable strategies to bettors. Previous studies have provided evidence for the existence of such inefficiencies. Since most studies cover only a few seasons, the question of whether market inefficiencies persist over time remains unanswered. We analyse the big five leagues in European association football for fourteen seasons to detect the occurrence and duration of market inefficiencies. While our results suggest that most biases do not persist for a long time, we still uncover profitable betting strategies throughout the full observation period.

Keywords: OR in sports, Sports betting, Efficient markets, Biases

1 Introduction

Sports betting markets underwent major changes during the last two decades. The introduction of online betting enabled bettors to put their money with bookmakers outside of their local market. Hence, former local monopolists lost power as bettors can now easily compare odds from different bookmakers online at low search costs. Bettors benefit from this increased competition since margins decreased and expected returns to bettors increased. As a consequence, bookmakers have increased their forecast precision to remain profitable despite facing increasing competition (Forrest et al., 2005; Štrumbelj and Šikonja, 2010).

Forecast precision is captured in the concept of efficient markets. If markets are efficient, asset prices contain all information available (Fama, 1970). Such efficient markets imply 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). Empirical 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 for one or multiple season(s) of data and have uncovered inefficient odds in different settings. Since studies typically only present a snapshot of relatively short periods of time, it remains to be investigated whether market inefficiencies persist over time or whether their appearance is of a temporary nature only.

This paper investigates the profitability of known betting strategies and provides an overview on possible inefficiencies. We analyse 14 seasons from 2005/06 to 2018/19 for the five major European (association) football leagues, namely the English Premier League, the French Ligue 1, the German Bundesliga, the Italian Serie A, and the Spanish La Liga. Our data supports previous findings on decreasing bookmaker margins over time and improved outcome prediction by bookmakers. Still, we uncover betting strategies that yield profits for the full period observed.

The paper is organised as follows. In the next section, we discuss the related literature. In Section 3, we describe the data and provide exploratory data analysis. Section 4 covers the empirical analysis and discusses profitable strategies for all the leagues considered. 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 (long-term) strategies. Such strategies exploit inefficient information processing by bookmakers, which result in biased betting odds. This section reviews research on top division European football only, as the empirical part of this paper is also devoted to it. There is a rich tradition of studies covering betting market inefficiencies, many of which focus on the motherland of football, England. 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* refers to the idea that bettors 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 by simply betting on the favourite. 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

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

systematically bet on the home team. Evidence on the existence of biased betting odds towards away teams has been shown by 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 only run 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. 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) find positive returns for betting on recently promoted teams at the start of seasons.

While many studies analyse data covering multiple seasons, others run their analysis by season. Very few studies split observation periods within seasons. The overview given in Table 1 supports the idea that inefficiencies can be temporarily detected for various leagues. This paper covers all biases discussed above for a very long period of time, namely from 2005 until 2019. While most inefficiencies only hold for a relatively short period of time, we do find some betting strategies that yield positive returns for the full time period.

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

The data set – taken from `www.football-data.co.uk` – covers all matches of the men's top professional 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 available. 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 very 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 follows:

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

with odds O_i, $i = h$ for a home win, $i = a$ for an away win, and $i = d$ for a draw. This 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*. Figure 1 (left panel) shows boxplots of the *Implied probabilities* for home and away wins. We observe higher implied probabilities for home teams, thus indicating that bookmakers expect a home field advantage. 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 only won about every fourth match (28.04%, see Table 2). These percentages only vary slightly across leagues. The covariate *Home* equals one for bets on the home team.

Since existing studies have revealed 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 *AgainstPromoted-Away*. We identify 26.3% of all observations 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.

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

	England	France	Germany	Italy	Spain	Total
observations	10640	10640	8568	10640	10640	51128
home win (%)	4962 (46.6)	4800 (45.1)	3884 (45.3)	4906 (46.1)	5058 (47.5)	23610 (46.2)
away win (%)	3054 (28.7)	2820 (26.5)	2524 (29.5)	2912 (27.4)	3024 (28.4)	14334 (28.0)
promoted (%)	2856 (26.8)	2796 (26.3)	2104 (24.6)	2856 (26.8)	2856 (26.8)	13468 (26.3)

To account for possible sentiment bias, we consider the difference in mean attendance in the corresponding season between the two opponents. Since we include two observations per match, the distribution is symmetric around zero, so 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 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 favourites often play at home and have a large fan base. The correlation between all other covariates is fairly low and hence negligible (see Table 3).

Market development over time

As argued above (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

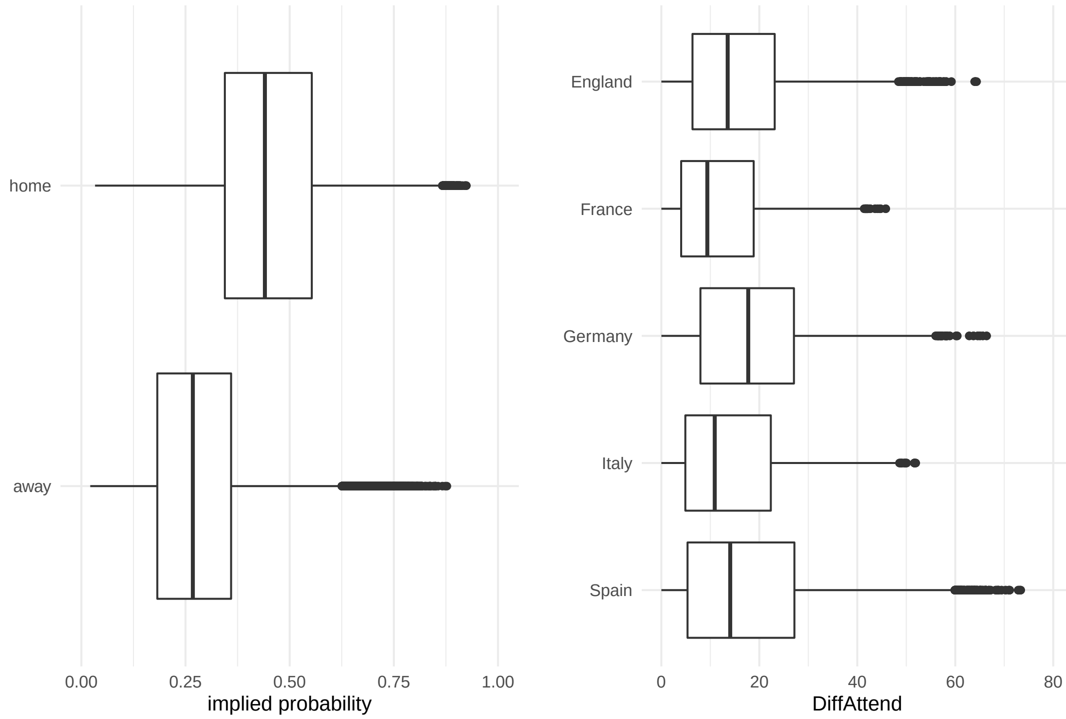

Figure 1: Boxplots on the probability as implied by bookmakers' odds (left panel) and boxplots on the differences in the attendance (right panel).

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

2005/06 to 2018/19 (left panel). Average margins decreased from more than 10% at the start of our observation period to about 5% in recent years in all leagues covered. The left panel in Figure 2 also indicates systematic differences in the margins between different leagues. To maintain profits with 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 the leagues contained in our data. Indicated by the grey dashed line, Brier scores over all leagues only improved 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 and whether any of these are profitable in the long run. 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. Finally, we analyse the profitability of betting strategies that result from the identified biases.

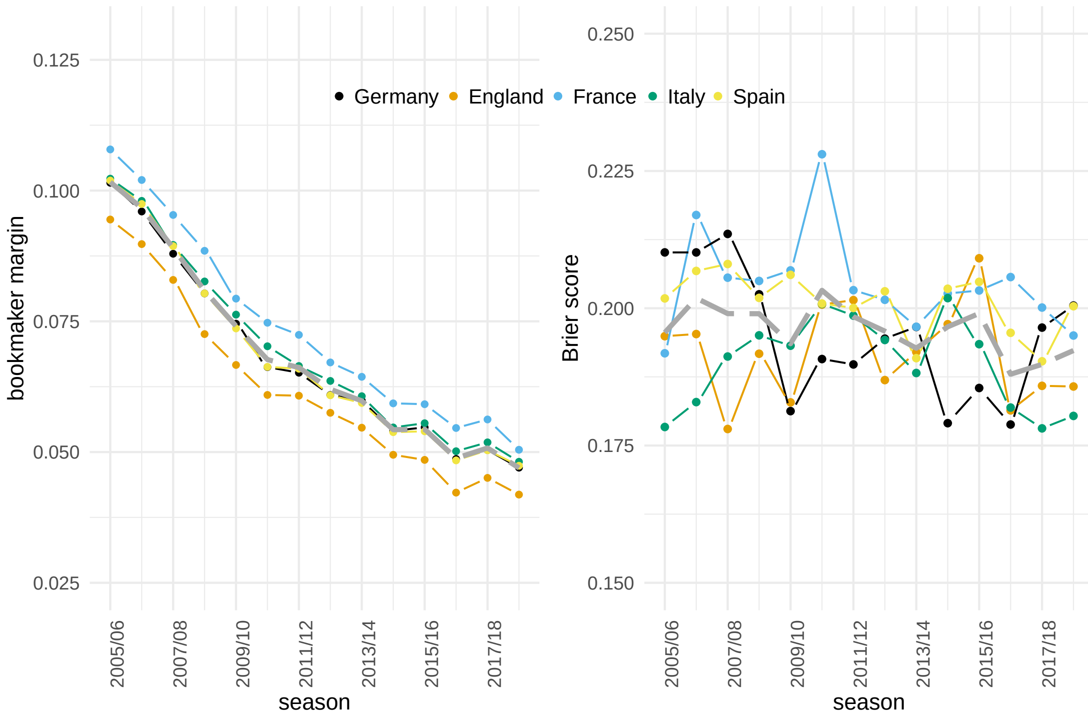

Figure 2: Bookmakers' margins and Brier scores during the period observed (season 2005/06 until 2018/19). Colours indicate different leagues, and the grey dashed lines show the average over all leagues.

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. Additionally, the *Implied probability* provides information on a possible favourite-longshot bias. It 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). To distinguish between the biases introduced in the literature overview, we 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.

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	...
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	...

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).

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. 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) with corresponding confidence intervals for zero difference in the average attendance between both teams.

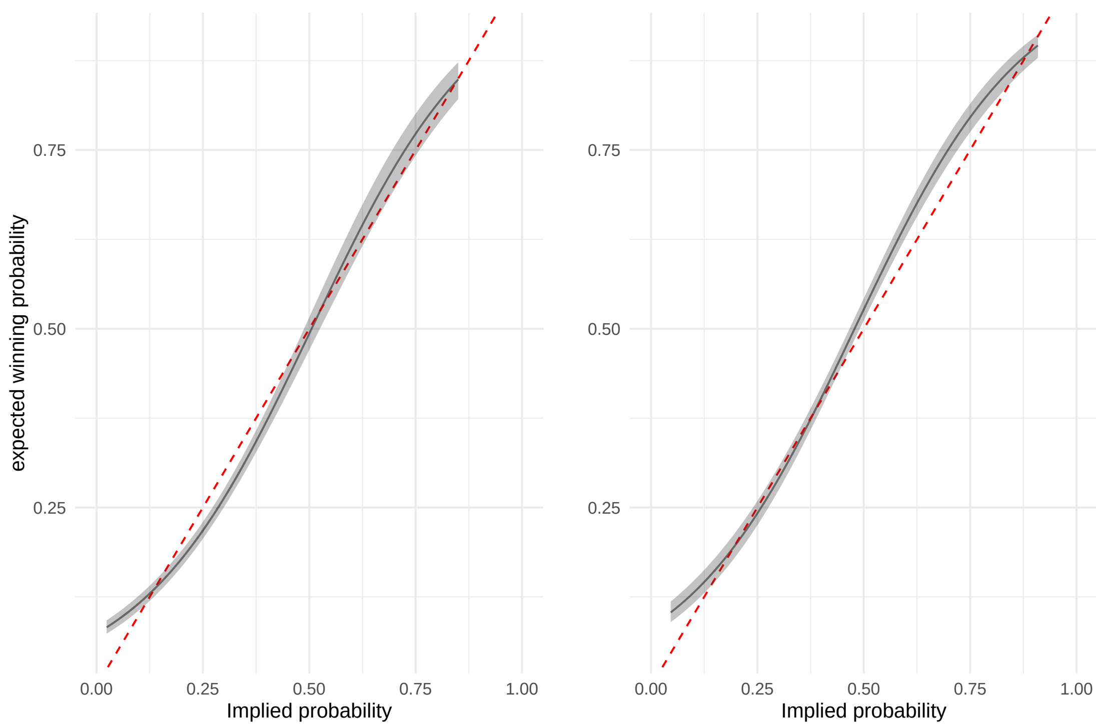

Figure 3: Probabilities for winning a bet under *Model 1* for away matches (left panel) and home matches (right panel).

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. Bookmakers undervalue favourites with implied probability between 0.5 and 0.8 in home games, whereas underdogs with implied probability between 0.2 and 0.4 are overvalued. This is in line with a favourite-longshot bias in the Premier League (Direr, 2011; 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 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 whole season, our results challenge prior findings that inefficiencies regarding the evaluation of promoted teams occur primarily at the very beginning of the season (Deutscher et al., 2018).

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

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

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).

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													

Our results confirm the strong explanatory power of *Implied probabilities*, as this effect is statistically significant in all seasons considered. Meanwhile, all other estimated effects are only significant in 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 fourteen 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,

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

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 sentiment bias, we see that for three consecutive seasons (2009/10 until 2011/12) a higher average attendance positively affects the chances to win a bet. This suggests the temporary existence of 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 the season and exist for single seasons only.

Further Leagues

The results on the biases analysed for further European top leagues can be obtained from the Appendix (see Tables 8 – 15) and are only briefly mentioned here. For all leagues considered, the models fitted to data of all seasons show 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), a sentiment bias exist in this but is limited to Spain according to our results (see Tables 8, 10, 12, and 14).

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

[4]Detailed figures are again shown upon request.

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 also confined to only three and respectively four single seasons 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 fourteen 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 the profits generated by these strategies. Table 7 presents the returns on invest (ROIs) 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]

In seven of fourteen 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

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

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

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**	**0.01**	**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**	-0.11	**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	**0.1**	-0.018	-0.048	-0.047
Italy	*Home*	-0.106	-0.122	-0.055	**0.016**	-0.01	-0.02	-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	*AgPromHo.*	-0.091	**0.045**	**0.28**	**0.019**	**0.093**	-0.132	**0.005**	**0.014**	**0.062**	**0.116**	-0.02	**0.142**	-0.055	**0.131**	**0.044**
France	*AgPromHo.*	-0.171	-0.029	-0.021	**0.05**	-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	-0.05	-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	-0.1	-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	-0.32	-0.061	-0.02
England	*AgPromAw.*	**0.193**	-0.357	-0.101	-0.125	-0.326	-0.099	-0.318	-0.205	-0.112	-0.088	**0.223**	-0.02	-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**	**0.15**	-0.033	-0.074	**0.151**	**0.188**	**0.157**	**0.231**	-0.2	-0.101	-0.272	-0.318	**0.027**	**0.005**
Italy	*AgPromAw.*	-0.014	-0.228	-0.14	**0.193**	-0.097	**0.046**	-0.292	**0.24**	**0.132**	-0.123	**0.144**	-0.077	**0.054**	-0.024	-0.013
Spain	*AgPromAw.*	**0.05**	**0.017**	-0.18	-0.036	-0.194	-0.145	-0.137	-0.037	-0.158	**0.267**	0	-0.123	-0.022	-0.01	-0.05
England	*OnPromHo.*	-0.289	-0.04	-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	-0.24	-0.434	**0.513**	**0.52**	-0.002	-0.135
Italy	*OnPromHo.*	-0.132	-0.034	**0.153**	-0.533	**0.111**	**0.046**	**0.116**	-0.192	-0.189	-0.2	-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	-0.35	**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**	-0.07	-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
England	*DiffAttend*	**0.012**	**0.117**	-0.011	**0.249**	**0.012**	-0.161	**0.08**	**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	-0.18	-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*	**0.07**	-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	**0.04**
Spain	*DiffAttend*	**0.003**	-0.076	-0.074	-0.067	**0.158**	-0.111	-0.054	**0.024**	-0.056	**0.046**	-0.012	-0.09	-0.03	-0.078	-0.028

Tables 10 and 14 in the Appendix). However, the related returns are not large enough to offset the average 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 league, 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, and Italy 2011/12 and 2016/17). Total returns over all seasons are also positive, and account for up to 4%. These results confirm the 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).

The different strategies for betting on games with promoted teams involved 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 fourteen seasons considered), and betting against promoted teams in their home games (return of 0.5% in Germany). However, 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.

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.

5 Discussion

While efficient markets should incorporate all available information, previous literature revealed promising strategies for bettors in European football. However, since most studies consider a narrow time period of data, the aim of this study has been to investigate whether inefficiencies are of a temporary nature only or persist over time. Fitting a logistic regression model to data from the top five European football leagues from seasons 2005/06 to 2018/19, we detect strategies leading to positive returns even in the long-run. Still, positive returns are more likely to be generated when considering shorter time periods, especially single seasons. Such possibilities already derive from the Brier scores presented in Section 3 (indicating prediction accuracy), which fluctuate over time. However, for seasons with relatively large Brier scores, positive returns are not always generated. For example, although Figure 2 suggests that positive returns are likely to be generated in France 2010/11, this does not hold true for that specific season, which is potentially driven by the fairly high amount of draws in that season. Comparing the development of betting markets to the generated returns, reduced margins over time do not increase chances of positive returns.

Over the full sample, the betting odds for the English Premier League, the German Bundesliga, and the Italian Serie A suffer from a sentiment bias, leading to positive returns, mainly driven by a small number of seasons. In addition, for England, Germany, and Spain the regression models uncover a significant home bias. Still, the home bias does hold for a few seasons only and does not lead to positive returns over the entire time period.

We further find positive returns for betting on/against promoted teams for a few seasons. However, our analysis does not suggest any systematic pattern regarding this bias. Specifically, in England and Germany, betting both on and against promoted teams can generate positive returns, typically at the beginning of a season. Our results indicate that bookmakers adjust their prices during the season, thus removing the possibility for bettors to generate positive returns. Whereas these findings are in-line with Deutscher et al. (2018), they vary substantially between leagues and seasons. Although we occasionally observe substantial returns when betting on/against promoted teams in all leagues, those strategies rarely lead to positive returns over the entire time period.

While market inefficiencies investigated in previous research often cover several different biases, some biases have not been explored yet. Specifically, more focus could be put on betting on games that feature specific settings. While we argue that recently promoted teams are harder to predict (especially at the start of seasons), the same argument can be made for recently relegated teams in lower divisions. In addition, the distinction between different periods of the seasons seems to be fruitful. Three periods appear to be particularly vulnerable for inefficiencies: First, the beginning of seasons when teams are hard to evaluate on previous performance. Second, the first few rounds right after the winter break constitute an interesting setting as teams had time to regroup, and potentially lose (or gain) momentum. Third, at the very end of seasons games are losing importance for some, but gain importance for other teams (Elaad et al., 2018). Such games are hard to predict and thus potentially lead to market inefficiencies. While Goddard and Asimakopoulos (2004) and Deutscher et al. (2018) pick up some of these issues, they are far from being researched enough.

6 Appendix

Table 8: 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 9: 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 10: 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 11: 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 12: 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 13: 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 14: 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 15: 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

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