Why do some soccer bettors lose more money than others?

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Abstract

Why do some soccer bettors lose more money than others? In an efficient prediction market, each gambler should break-even before costs (but losing a constant amount after costs, reflecting the bookmaker's margin). Previous empirical studies across numerous sports betting markets show that bets on longshots tend to lose more than bets on favourites (favourite-longshot bias). We use 163,992 soccer odds from ten European leagues to test plausible hypotheses around why some soccer bettors lose more money than others. Are soccer bettors with above average losses simply biased, or are their losses driven by betting on events that are inherently unpredictable? We confirm the existence of favourite-longshot bias in soccer in this sample, but find another surprising feature of betting on longshots. As measured by the Brier score, bookmakers' odds were better predictors of longshots than favourites, suggesting another potential channel whereby bettors' preference for betting on longshots may cost them dearly.

1. Introduction

Soccer betting is big business, with online sports betting companies producing gross gambling revenues (stakes minus winnings) of over €6 billion in 2015 (European Gambling and Betting Association, 2016). For this simple economic reason, it is important to find out why soccer bettors lose money. But betting markets are also often studied as simple real-world domains for testing the economic theory of financial markets (Lessmann, Sung, & Johnson, 2009; Sauer, 1998). In this paper, we use a large dataset of 163,992 soccer odds from ten top European leagues to test plausible hypotheses around why some soccer bettors lose more money than others. Are soccer bettors with above-average losses simply biased, or are their losses driven by betting on events that are inherently unpredictable? Recent notable upsets in both soccer and politics illustrate how the big data approach used in this paper contributes to the forecasting literature.

There is one basic reason why most sports bettors must lose. Unlike in financial markets, the average sports bettor must lose in order to provide bookmakers with their positive margin. (Although financial intermediaries also have positive margins, the stock market is a positive-sum game, while sports betting is a zero-sum game.) Bookmakers are traditionally thought to set odds on each potential outcome to create a "balanced book," meaning that their gross gambling revenue is the same for any outcome of the sporting match (Stark & Cortis, 2017). If markets were perfectly efficient, then bettors' losses on both likely and unlikely events should be equal. Otherwise, smart bettors could obtain better-than-average returns. However, unlikely outcomes appear to be overestimated by the average bettor. Better-than-average returns can generally be obtained by betting on favourites (although not necessarily enough to overcome the bookmaker's margin). This anomaly, called the favourite-longshot bias, describes the tendency for gamblers to over-estimate the likelihood of longshots winning and under-estimate favourites (Ali, 1977; Thaler & Ziemba, 1988). There is an extensive

literature on favourite-longshot bias, with most research finding that longshots have greater long-run losses than favourites (Ali, 1977; Bird & McCrae, 1987; Gandar, Zuber, & Johnson, 2001; Griffith, 1949; Hausch, Ziemba, & Rubinstein, 1981; Winter & Kukuk, 2006; Vaughan Williams, 1999) . More recently (Vaughan Williams, Sung, Fraser-Mackenzie, Peirson, & Johnson, 2016) found evidence of the favourite-longshot bias in poker players.

Nevertheless, some exceptions have been found, with above-average losses for favourites in Asian racecourses (Coleman, 2004; Walls & Busche, 2003), baseball (Woodland & Woodland, 1994), and sometimes in soccer (Gil & Levitt, 2012). However, other studies of soccer betting have found above-average losses for longshots, in line with the majority of research in other sports (Cain, Law, & Peel, 2003; Constantinou & Fenton, 2013; Deschamps & Gergaud, 2012; Graham & Stott, 2008; Vlastakis, Dotsis, & Markellos, 2009). One-off cases, such as Leicester City winning the 2016 English Premier League as 5000:1 outsiders, help to illustrate how longshots may not universally be bad bets. Longshots are risky for bookmakers if incorrectly priced. Bookmakers may well find it more difficult to accurately price longshots in dynamic sporting environments, where the "true" odds are constantly changing.

Most of the favourite-longshot bias literature in soccer used relatively small sample sizes, potentially explaining why contrasting results occur. In this paper we analyse a total sample of 163,992 soccer odds from 41,003 matches (for ten leagues over twelve seasons). The first aim of this research therefore is to examine whether in this large sample betting markets efficiently price events, and if they do not, whether longshots or favourites suffer above-average losses.

We also use this large dataset to explore a novel interpretation of favourite-longshot bias. It is possible that bettors' results are driven not by bettors' misperceptions, as argued in the previous literature, but also by inaccuracies in bookmakers' odds. Likely events are quite possibly easier for bookmakers to predict, given there will be a larger sample of likely events in previous history to base estimates on. The unpredicted political events of 2016, The UK's referendum over Brexit and Donald Trump's election both being given a 25% on polling day (Griffin, 2016), highlight that "unlikely" events can be incredibly hard to predict well, even for professional forecasters.

2. Methodology

2.1 Data

The data consist of twelve seasons from 2005/06 to 2016/17 for ten popular European club leagues (Table 1). In addition to the English Premier League, we also include the English Championship (second tier) and the Scottish Premiership, as the United Kingdom is Europe's largest betting market (Hudson, 2014).

The data consist of the full-time result, the average '1X2' odds ('1' signifies a home team win, 'X' a draw and '2' an away team win) and average 'Over and Under 2.5 Goals' odds (bets on whether more/less than two goals are scored in a match). As the over and under odds are mutually exclusive, we focus solely on overs (that is odds on three or more goals), since the results on the unders markets will be their inverse. The average odds for a number of

bookmakers as collated by BetBrain.com were used. We did not notice a trend in the mean number of bookmakers used over time, but an increase in the minimum number of bookmakers sampled was evident. A small number of matches were excluded, as shown in the appendix.

Table 1: Number of Bookmakers used for Match Odds

Division	Mean	Minimum	Maximum
Belgian	38.74	8	62
Eng. Champ.	41.85	17	74
Eng. Prem.	43.45	9	79
French	41.99	10	73
German	42.48	11	77
Italian	42.25	1	77
Dutch	40.29	13	68
Portuguese	38.47	1	64
Scottish	40.07	1	68
Spanish	42.91	25	78
Total	41.52	1	79

2.2 Determining probabilities, profit and accuracy

Bettors place wagers on particular outcomes and earn money if it occurs. The value of the prospective prize in relation to the wager results in a subjective probability - the likelihood of each outcome as perceived by the betting market. Prospective prizes are communicated via "odds", as explained in this section.

One method of displaying odds is the European/Decimal format, where the odds represent the total prospective prize from a bet of €1. European odds are conveniently also the inverse of the probability of the outcome. For example, the odds for rolling a fair die are 6 for each outcome (each of the six sides has probability = 1/6 of occurring on a single roll). However, a bookmaker would place this at a lower value, say 5.8. This results in the sum of implied probabilities being $6(5.8^{-1}) = 103.45\%$ where the 3.45% can be defined as the bookmaker margin (denoted k). It can be proven that the expected profit of a bookmaker as a percentage of wagers made is $\frac{k}{k+1}$ (Cortis, 2015), being $\frac{1}{30}$ here. Consider that if a €5 bet is placed on each outcome, $5 \times 5.8 = €29$ is paid out in winnings with €1 retained by the bookmaker as profit. Bettors lose a thirtieth of their wagers in expectation.

Implied probabilities from bookmakers' odds for a complete set of outcomes in an event must sum to greater than 1, in order for bookmakers to avoid arbitrage (Cortis, 2015). The higher the sum of probabilities beyond 1, the higher the bookmaker's profit margin against a random bettor (Kuypers, 2000). Across the full dataset, we find average 1X2 probabilities summing to 1.0771, and Over and Under 2.5 probabilities summing to 1.0699. This finding aligns with prior research, showing that the bookmaker profit margin tends to increase with the number of possible events (three for 1X2, two for Over and Under 2.5; (Ayton, 1997; Newall P. W.,

2015; Newall P. W., 2017). The average sum of probabilities gradually declined over the time-period studied, as illustrated in Figure 1, showing that these betting markets have become more competitive over time.

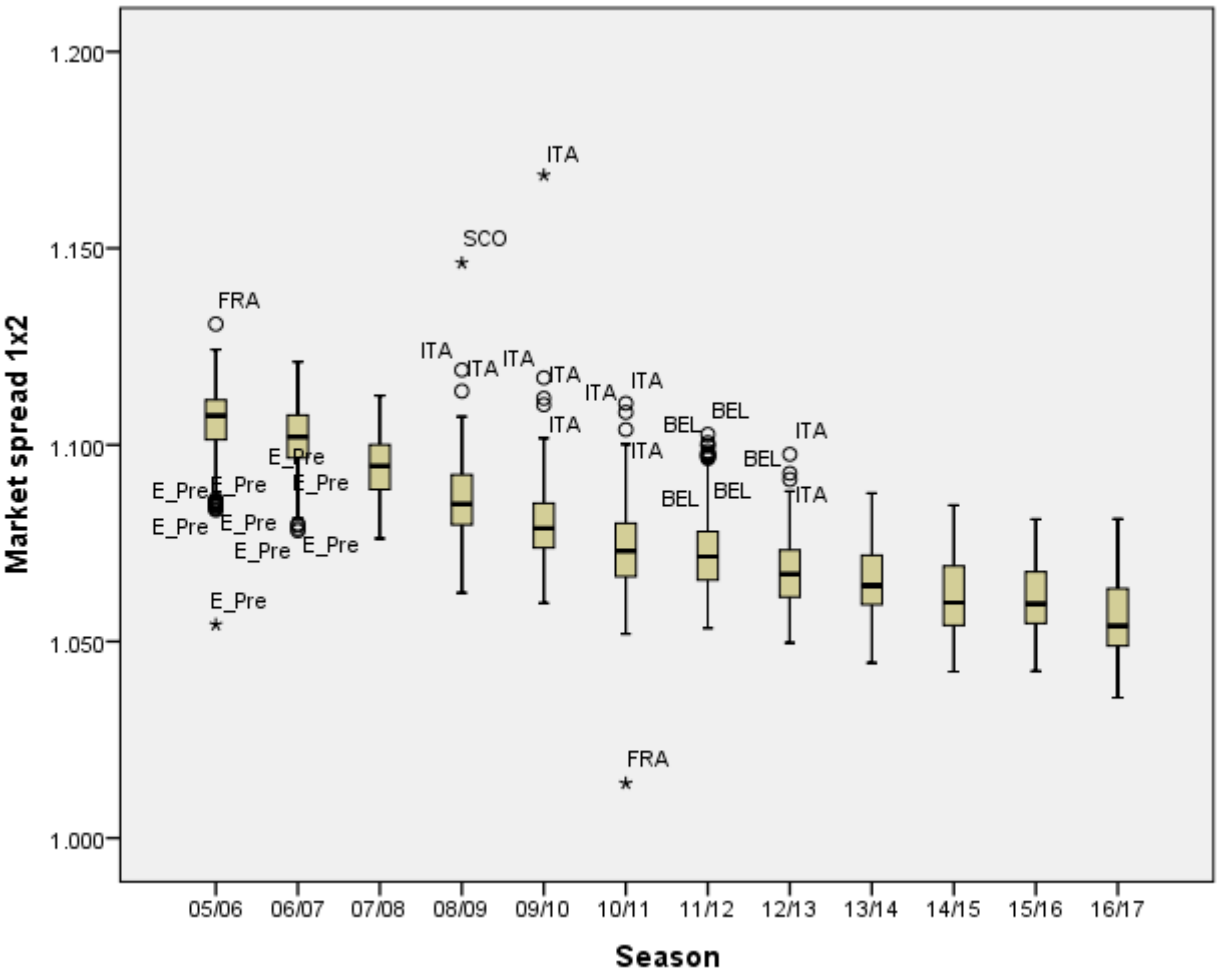

Figure 1: Market Spread over seasons for 1X2 odds

An accurate probabilistic forecast must be coherent: probabilities must sum to 1 for a complete set of events (Seidenfeld, 1985). Therefore, there are two different interpretations of probability[1]:

- the raw probability directly implied by the betting odds (π);
- the subjective probability of an outcome[2] (p_s), which is the implied probability adjusted for the bookmaker margin (k);

Raw probabilities reflect the bookmaker profit margin, and therefore sum to greater than 1 for a complete set of events (Cortis, 2015). Subjective probabilities adjust for the bookmaker profit margin, and are therefore "coherent": summing to 1 for a complete set of events.

[1] Notation similar to Cortis (2015) and Shin(1991) is used.

[2] A proportional relationship between subjective and implied probabilities such that $p_s = \frac{\pi}{1+k}$ is assumed similar to Archontakis & Osborne (2007) and Cortis, Hales, & Bezzina (2013).

Subjective probabilities will be compared with realized "objective probabilities": the actual post-event objective probability of an outcome (p_o), estimated to be the number of actual occurrences as a proportion of the number of observations made.

Therefore, objective probabilities are estimated based on the relative frequency of events in the dataset. For example, if the team Manchester United won 23 of 50 matches, then the objective probability of Manchester United winning would be $\frac{23}{50} = 0.46$ Given a large enough dataset, measured objective probabilities should coincide with "true" objective probabilities, via the law of large numbers.

We measure losses by assuming a "unit" bet of €1 is made on each outcome. This can be defined as $\frac{1}{n}\sum\left(1 - \frac{I}{\pi}\right)$ where I is a Boolean variable (which is 1 if the outcome occurs, and 0 otherwise) while and n is the number of observations measured over). For example, assume four events with odds of 3.6, 3.8, 3.5 and 3.4, and only the first outcome with odds of 3.6 occurred, then the percentage loss is $\frac{1}{4}[(1 - 3.6) + 1 + 1 + 1]$ = 10%. We expect bets to result in a loss, reflecting the bookmaker profit margin. Favourite-longshot bias will be tested for by examining if losses vary as odds change.

To test the hypotheses related to prediction accuracy, we use the Brier Score (Brier, 1950). This is defined as the mean square difference between the subjective probability and actual outcome (i.e. $\frac{\sum(p_s - I)^2}{n}$). A Brier score can vary between zero and one, with more accurate predictions reflected by Brier scores closer to zero. For example, if the home team is predicted to win with probability = 1 and it does, this provides a Brier score of zero. But if the home team does not win, this provides the maximum Brier score of one. As another example, consider that if three matches were predicted 22%, 23% and 24% likely to be a home win and only the last one ended with the home team winning, the Brier Score is 0.2263. Intermediate predicted probabilities provide smaller gains from accurate predictions, but with smaller increases in the Brier score for inaccurate predictions. For example, a predicted probability of 0.5 provides a Brier score of 0.25 whether the home team wins or not.

2.3 Subdividing the range of probabilities

Given the continuous nature of the data, we needed to group "similar" data points together in order to test our hypotheses. We chose to subdivide data points into twenty "ranges" of probabilities. Twenty ranges were considered as ideal as a smaller number of ranges may not have statistical significance while larger ranges may not show any trends. Tests made on ten and thirty ranges yielded similar results.

If the ranges were based on equal subjective probabilities of 5% range, some would have significantly high sample sizes (for example there are 36,831 observations in the 25%-30% range) and other significantly small samples (no odds implied a subjective probability above 95%). At a total of 163,992 odds were observed, the ideal would be to have 8,200 observations per range (20*8,200). We used an iterative process, such that each range would be between half and twice this value resulting in no range more than quadruple size of any other. We believe this is a methodological improvement in this field of research. Indeed much

research subdividing the ranges of probabilistic outcomes leads to unstable results due to small sample sizes. For example, it is very rare to have a big favourite in horseracing (Ali, 1977).

The iterative process is as follows:

1. Subdivide into twenty equal ranges of subjective probabilities.
2. Find the range with the largest number of odds observations.
    a. If this is more than 16,399,
        i. subdivide it into two ranges by taking the mid-point of the subjective probability range, and
        ii. merge the range with the lowest number of odds observations to the smallest adjacent range.[3]
    b. If the largest range has less than 16,399 observations, find the smallest range. If this has less than 4,100 observations, then
        i. merge this range to the smallest adjacent range, and
        ii. subdivide the largest range in two by taking its mid-point.
3. Repeat step 2 until all total odd ranges have between 4,100 and 16,399 observations.

The final ranges of subjective probabilities, together with the number of observations are shown in Table 2. As can be seen, the first range of the least-likely events ranges from 0 to 0.15, and contains 9,126 total observations. This probability range is relatively wide, because there are relatively few events that bookmakers consider this unlikely. There are many more events of intermediate odds ranges, which is why for example the procedure bins 8,378 events in the range 0.28125 to 0.2875.

This process does have its limitations, since not all outcomes have equal dispersion. For example, the subjective probabilities for draws ($\mu_{p_s} = 0.264, \sigma_{p_s} = 0.042$) and overs ($\mu_{p_s} = 0.498, \sigma_{p_s} = 0.071$) are less dispersed than home ($\mu_{p_s} = 0.446, \sigma_{p_s} = 0.160$) and away ($\mu_{p_s} = 0.290, \sigma_{p_s} = 0.142$).

Table 2: Number of Observed Odds

p_s	Total	Home	Draw	Away	Overs
[0,0.15)	9,126	1,477	1,165	6,484	
[0.15,0.2)	8,726	1,379	2,689	4,657	1
[0.2,0.25)	13,125	1,609	5,695	5,821	
[0.25,0.2625)	5,348	488	3,109	1,751	
[0.2625,0.275)	8,066	537	5,685	1,844	
[0.275,0.28125)	6,331	272	5,193	866	
[0.28125,0.2875)	8,378	309	7,259	810	
[0.2875,0.3)	8,708	664	6,387	1,657	
[0.3,0.325)	8,629	1,654	3,673	3,298	4
[0.325,0.35)	4,864	1,860	69	2,889	46
[0.35,0.4)	11,418	5,761	37	3,519	2,101

[3] Using the first iteration as an example: The 25%-30% range was split into ranges of 25%-27.5% and 27.5%-30% while the smallest range of 95%-100% was added to the adjacent range 90%-95%.

[0.4,0.425)	7,855	3,026	9	1,264	3,556
[0.425,0.45)	9,798	3,094	10	1,025	5,669
[0.45,0.475)	10,115	2,834	4	765	6,512
[0.475,0.5)	8,538	2,352	4	655	5,527
[0.5,0.525)	7,016	2,132	3	574	4,307
[0.525,0.55)	6,524	1,907	3	544	4,070
[0.55,0.6)	9,419	2,876	4	944	5,595
[0.6,0.65)	5,089	2,048	3	690	2,348
[0.65,1)	6,919	4,723	1	945	1,250
Total	**163,992**	**41,002**	**41,002**	**41,002**	**40,986**

2.4 Hypotheses

Three variables are being compared: the subjective probability of an outcome, bettors' losses, and prediction accuracy. The existence of a longshot bias would imply that bettors' losses are lower for more likely events (H^a_1):

H^a_1: Bettors will lose more on unlikely than likely events (longshot bias). This is measured by the profitability of the unit bet strategy across different odds ranges. There will be a negative correlation between subjective probabilities and losses on unit bets.

Secondly, given that they will have a larger sample of similar events to use from previous history, we expect bookmakers to be able to set odds that are more accurate for more likely outcomes (H^b_1):

H^b_1: Predictions will be more accurate for likely than unlikely events. There will be a negative correlation between Brier scores and subjective probabilities.

Moreover, we envisage that accurate predictions are easier to manage for bookmakers and this is used as an advantage over bettors (H^b_1). Therefore:

H^c_1: Bettors will lose more on events that are predicted accurately. There will be a negative correlation between bettors' losses and the Brier score.

We use two-tailed hypothesis tests for each relationship and also consider each league separately. In order to limit the effects of ranges with a small number of observations, we re-examine the two-tailed hypothesis on only the ranges with at least 50 observations.

3. Analysis and Results

3.1 General and Match Odds (1X2)

Figure 2 compares the subjective and objective probabilities. In an efficient market, the two probabilities would be equal and fit around a 45-degree line passing through the origin (zero favourite-longshot bias). The graph shows a trend of unlikely events characterised by subjective probabilities that are slightly higher than objective probabilities. The betting market appears to overestimate the likelihood of unlikely events. Contrastingly, likely events have implied probabilities that are lower than objective probabilities. The betting market appears to underestimate the likelihood of likely events. This observation of longshot bias, in

a large sample, corresponds to much of the previous literature on soccer (Cain, Law, & Peel, 2003; Constantinou & Fenton, 2013; Deschamps & Gergaud, 2012; Graham & Stott, 2008; Vlastakis, Dotsis, & Markellos, 2009).

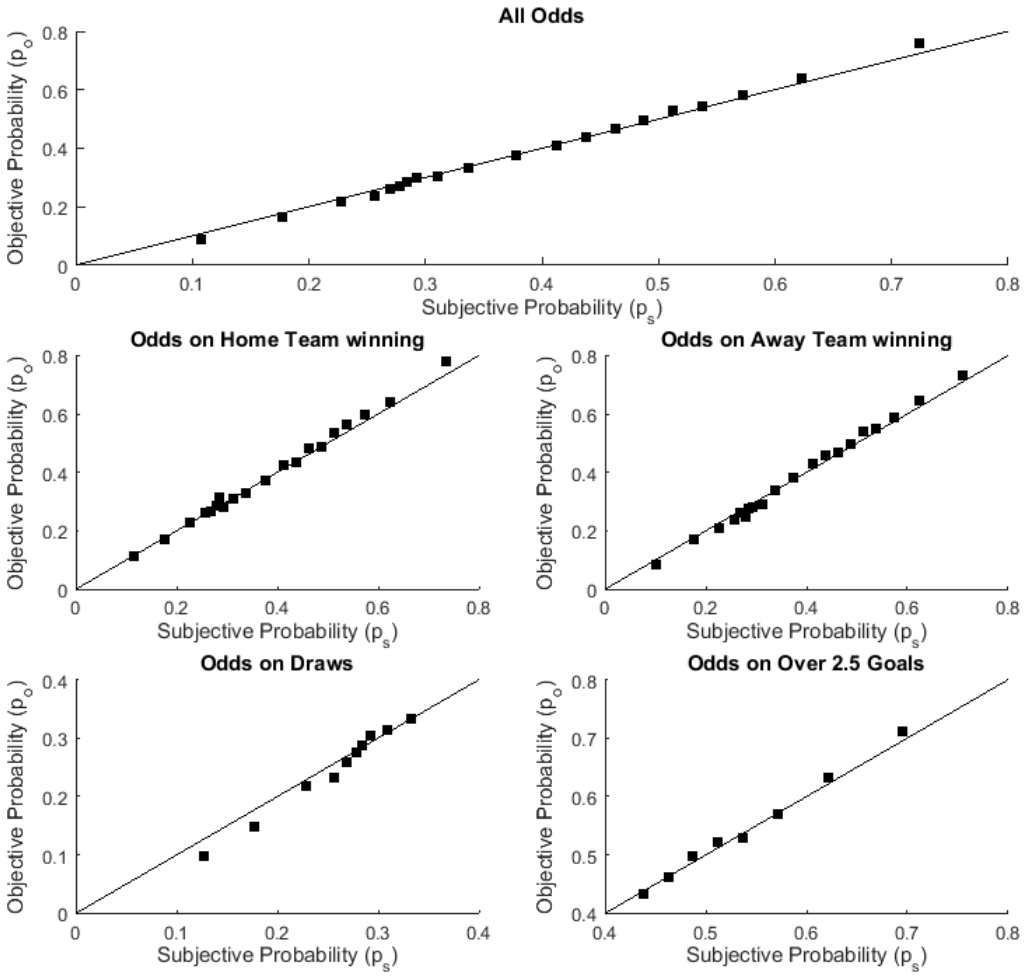

Figure 2: Relationship between p_s and p_o

Table 3: Bettor Losses for Unit Bets per Odd and Brier Scores

Subjective Prob (p_s)	Total			Home			Draw			Away			Overs		
	Actual Loss	Exp Loss	Brier Score	Actual Loss	Exp Loss	Brier Score	Actual Loss	Exp Loss	Brier Score	Actual Loss	Exp Loss	Brier Score	Actual Loss	Exp Loss	Brier Score
[0,0.15)	26.2%	6.9%	0.081	11.1%	6.8%	0.099	28.6%	6.3%	0.089	29.2%	7.1%	0.075			
[0.15,0.2)	13.8%	7.1%	0.137	8.7%	7.0%	0.142	21.8%	6.9%	0.127	10.6%	7.3%	0.141	-42.0%^^^	76.8%	0.700
[0.2,0.25)	11.4%	7.0%	0.169	5.1%	7.1%	0.177	10.9%	6.8%	0.171	13.7%	7.2%	0.166			
[0.25,0.2625)	14.5%	7.1%	0.181	5.6%	6.9%	0.193	16.2%	7.1%	0.179	13.8%	7.1%	0.181			
[0.2625,0.275)	10.1%	7.2%	0.193	8.5%	7.0%	0.195	10.7%	7.2%	0.192	8.8%	7.2%	0.194			
[0.275,0.28125)	9.5%	7.5%	0.198	3.4%	6.8%	0.205	8.6%	7.5%	0.199	17.2%	7.2%	0.187			
[0.28125,0.2875)	6.7%	7.4%	0.204	2.6%	7.0%	0.216	6.7%	7.5%	0.205	10.7%	7.3%	0.199			
[0.2875,0.3)	5.4%	6.9%	0.209	10.3%	6.9%	0.203	3.3%	6.8%	0.211	11.3%	7.2%	0.202			
[0.3,0.325)	9.4%	7.3%	0.211	8.4%	7.1%	0.213	5.7%	7.5%	0.215	14.2%	7.2%	0.206	-50.0%^^^	5.8%	0.284
[0.325,0.35)	8.1%	7.3%	0.222	9.8%	7.2%	0.220	7.7%^	8.2%	0.223	7.0%	7.3%	0.224	10.4%^^	6.2%	0.219
[0.35,0.4)	7.4%	7.2%	0.234	8.3%	7.3%	0.233	14.7%^^	8.4%	0.227	4.7%	7.2%	0.236	9.4%	6.8%	0.234
[0.4,0.425)	8.2%	7.0%	0.241	4.8%	7.3%	0.244	27.2%^^^	9.5%	0.228	3.4%	7.1%	0.245	12.7%	6.8%	0.238
[0.425,0.45)	7.2%	6.9%	0.246	7.7%	7.2%	0.246	-4.7%^^	9.2%	0.254	2.2%	6.9%	0.249	7.9%	6.7%	0.245
[0.45,0.475)	5.6%	6.7%	0.249	3.1%	7.2%	0.250	2.0%^^^	8.7%	0.249	5.9%	6.9%	0.249	6.7%	6.5%	0.248
[0.475,0.5)	5.1%	6.6%	0.250	7.4%	7.3%	0.250	6.5%^^^	10.0%	0.249	5.2%	7.1%	0.250	4.1%	6.2%	0.250
[0.5,0.525)	3.7%	6.6%	0.249	2.7%	7.2%	0.249	41.7%^^^	9.4%	0.253	2.5%	7.2%	0.249	4.3%	6.1%	0.249
[0.525,0.55)	5.9%	6.7%	0.248	2.9%	7.3%	0.247	-70.0%^^^	9.3%	0.217	5.0%	7.1%	0.248	7.6%	6.4%	0.249
[0.55,0.6)	5.5%	6.9%	0.243	2.9%	7.2%	0.241	21.8%^^^	9.9%	0.248	4.6%	7.1%	0.242	7.0%	6.7%	0.245
[0.6,0.65)	4.7%	6.9%	0.231	4.9%	7.0%	0.230	-44.0%^^^	9.9%	0.140	3.3%	6.9%	0.229	5.0%	6.8%	0.232
[0.65,1)	2.0%	6.8%	0.178	1.1%	6.9%	0.169	-29.0%^^^	14.4%	0.113	3.5%	6.5%	0.193	4.3%	6.6%	0.203
Total	8.3%	6.9%	0.214	5.6%	7.2%	0.218	9.8%	7.1%	0.189	12.5%	7.2%	0.180	6.9%	6.5%	0.244

^ ≤100 Observations, ^^ ≤50 observations, ^^^ ≤10 observations

Profit/Loss columns show the percentage profit/loss made if a unit bet is placed on odds recorded within this range. Expected Profit/Loss columns are derived from the bookmaker margin.

Table 3, showing the actual losses, expected losses as defined by Cortis (2015), and the Brier Scores for different ranges and the four outcomes, implies that our first hypothesis (H^a_1) may be true. Although the expected loss, determined by the betting margin, is somewhat similar for all subjective probability ranges, the losses made for lower probability outcomes are much higher than higher probability outcomes. This is corroborated by the majority of significant correlations between profits and observed probabilities being negative (Table 4). Excluding ranges with less than fifty observations, only the German Bundesliga does not seem to exhibit any evidence of the longshot bias. Otherwise we do not find any major discrepancies between different leagues.

Table 4: Correlation between Losses and Observed Proportions (p_o)

		Overall	Home	Draw	Away	Over
All Leagues	All	-0.786***	-0.484**	-0.514**	-0.781***	0.607**
	>50			-0.922***		-0.650***
Belgian	All	-0.555**	-0.134	0.201	-0.410*	0.474
	>50		-0.004	-0.770*	-0.275	0.398
Dutch	All	-0.507**	0.075	0.532	-0.586***	0.056
	>50		0.095	-0.085	-0.572**	-0.391
Eng. Prem	All	-0.742***	0.161	-0.926***	0.443*	-0.547
	>50		0.052			-0.388
Eng. Cham	All	-0.588***	0.013	-0.925***	0.482**	0.563
	>50		-0.001	-0.263	0.343	-0.516
French	All	-0.665***	-0.222	-0.862***	0.647***	0.060
	>50		-0.152	-0.391	0.607**	-0.520
German	All	-0.111	0.274	-0.753**	-0.227	-0.508
	>50		0.294	-0.750*		0.176
Italian	All	-0.707***	-0.669*	-0.498**	0.654***	-0.546
	>50		-0.675*	-0.503		
Port.	All	-0.750***	-0.553**	0.127	0.616***	-0.410
	>50		-0.859*	-0.805**	0.594***	-0.686*
Scottish	All	-0.410*	0.044	-0.514	0.063	0.630*
	>50		-0.238	-0.413	0.317	-0.098
Spanish	All	-0.757***	-0.064	-0.478	0.342	0.559*
	>50		-0.015	-0.860***	0.269	-0.207

**** significant at p < 0.01, ** significant at p < 0.05, * significant at p < 0.1*
All values proven significant using a two-tailed test.

Table 55: Correlation between Brier Scores and Observed Proportions (p_o)

		Overall	Home	Draw	Away	Over
All Leagues	All	0.644***	0.573**	0.283	0.703***	-0.679**
	>50			0.992***		-0.577
Belgian	All	0.616***	0.521**	0.567	0.695***	-0.826***
	>50		0.301	0.949***	0.895***	-0.758*
Dutch	All	0.694***	0.471**	0.367	0.776***	-0.695*

	>50		0.509**	0.968***	0.770***	-0.922**
Eng. Prem	All	0.656***	0.444*	0.995***	0.707***	0.358
	>50		0.554**			-0.396
Eng. Cham	All	0.742***	0.690***	0.970***	0.552**	0.702**
	>50		0.561**	0.896**	0.941***	0.643
French	All	0.683***	0.659***	0.977***	0.705***	-0.358
	>50		0.642***	0.946***	0.954***	-0.180
German	All	0.663***	0.541**	0.983***	0.623***	0.315
	>50		0.562**	0.985***		-0.913***
Italian	All	0.652***	0.630***	0.286	0.656***	-0.676**
	>50		0.633***	0.966***		
Port.	All	0.577***	0.542**	0.595*	0.675***	-0.590*
	>50		0.557**	0.985***	0.666***	-0.091
Scottish	All	0.646***	0.459**	0.944***	0.540**	0.636*
	>50		0.563**	0.936***	0.543*	0.192
Spanish	All	0.578***	0.420*	0.783***	0.684***	-0.727**
	>50		0.409	0.983***	0.655***	-0.753**

**** significant at p < 0.01, ** significant at p < 0.05, * significant at p < 0.1*
All values proven significant using a two-tailed test

The results for our second hypothesis comparing prediction accuracy with event probability (Table 5), imply that the Brier Score is higher for higher-probability outcomes. The lower Brier Score for lower-probability outcomes indicates that unlikely events actually seem to be predicted more accurately than likely events. There is evidence of a contradictory hypothesis, against our second hypothesis.

Our third hypothesis, that bettors will lose more on accurately predicted outcomes, can be examined via Table 6's correlations between Brier Scores and losses. All significant correlations between Brier Scores and losses (Table 6) are negative for ranges with at least fifty observations. Less accurate odds (higher Brier Scores) lead to lower losses for bettors.

Draws warrant special attention as correlation coefficients tend to be higher. Past research has shown a negative longshot bias and lower losses than backing other outcomes in English Soccer (Snowberg & Wolfers, 2010). Contradictory to this, our results based on European soccer imply lower losses for most ranges but higher overall percentile losses on unit bets than backing home wins (Table 3). One can notice some one-off profits within highly likely ranges. For example there was only one game that was deemed more than 65% likely to be a draw, (and which did indeed end in a draw, Table 3). Moreover, Figure 2 displays a more acute longshot bias for draws than other outcomes. Bettors' losses on draws tend to be lower for more likely outcomes and inaccurate predictions (Tables 4 & 6), possibly due to draws being more inaccurate for likely cases (Table 5). This is in agreement with the general belief that draws are considered the most challenging outcome to predict (Pope & Peel, 1989).

Table 6: Correlation between Brier Scores and Losses

		Overall	Home	Draw	Away	Over
All	All	-0.820***	-0.342	0.140	-0.870*	-0.682**

Leagues	>50			-0.959***		0.119
Belgian	All	-0.544**	-0.384	-0.692**	-0.454*	-0.434
	>50		-0.071	-0.931***	-0.576**	-0.336
Dutch	All	-0.715***	-0.392*	-0.591	-0.847***	-0.464
	>50		-0.181	-0.327	-0.850***	0.641
Eng. Prem	All	-0.719***	-0.285	-0.954***	-0.586*	-0.954***
	>50		0.046			-0.351
Eng. Cham	All	-0.718***	-0.268	-0.989***	-0.107	0.825***
	>50		-0.119	-0.651	-0.555**	-0.557
French	All	-0.707***	-0.469**	-0.933***	-0.730***	-0.655**
	>50		-0.416*	-0.665*	-0.728***	-0.151
German	All	-0.114	0.030	-0.854***	-0.064	-0.923***
	>50		0.248	-0.852**		0.053
Italian	All	-0.802***	-0.793***	0.155	-0.711*	0.543
	>50		-0.792***	-0.704**		
Port.	All	-0.802***	-0.721***	-0.719**	-0.606***	-0.922***
	>50		-0.767***	-0.891***	-0.623***	-0.114
Scottish	All	-0.600***	-0.447*	-0.766**	-0.505**	0.762**
	>50		-0.328	-0.705*	-0.594**	0.236
Spanish	All	-0.689***	-0.163	-0.908***	-0.543**	-0.928***
	>50		-0.142	-0.938***	-0.495**	0.259

**** significant at p < 0.01, ** significant at p < 0.05, * significant at p < 0.1*
All values proven significant using a two-tailed test

3.2 Contrasting results in the overs market

The overs market, characterised by relatively low variability in subjective probabilities, displayed some conflicting results.

For Belgian, Dutch, German, Italian and Spanish leagues, bookmakers tended to be less accurate in predicting unlikely outcomes than likely ones (providing evidence in support of our second hypothesis, contrasting to the rest of the data, see Table 6). Some of the difficulty stems from the fact that these five leagues have among the highest standard deviation of goals scored per match from the ten leagues sampled (Table 7).

Table 7: Total Goal Distribution per League

League	Goals/match
Belgian Pro League	2.73 (± 1.65)
Dutch Eredivisie	3.05 (± 1.74)
English Prem	2.67 (± 1.67)
English Cham	2.58 (± 1.59)
French Ligue 1	2.40 (± 1.56)

League	Goals/match
German Bundesliga	2.87 (± 1.71)
Italian Serie A	2.63 (± 1.64)
Portuguese Prim. Liga	2.45 (± 1.59)
Scottish Premier	2.65 (± 1.64)
Spanish La Liga	2.73 (± 1.71)

4. Conclusion

We found evidence to sustain two of our three hypotheses: bettors lose more on unlikely than likely events (longshot bias), and bettors lose more on events that are more accurately

predicted by bookmakers. In contrast to our second hypothesis, unlikely events were actually predicted more accurately by bookmakers than likely events.

Longshot bias results pose the following question: why haven't markets adjusted accordingly, given that this bias has been discovered in studies decades ago, and the market efficiency prediction from economic theory? We think that the possibility of arbitrage results in odds inaccuracy as the "wisdom of the crowd" is followed. The betting market is sufficiently liquid such that bookmakers cannot offer odds that create arbitrage opportunities for smart bettors. For example, even if one bookmaker is certain that the probability of a two-outcome event is equally likely, it would be hesitant to offer odds at evens if the rest of the market is pricing it at a ratio of 1:3 for outcomes A and B as it would risk having all wagers on Outcome B. Although profitable in the long run, it is more likely to result in bookmaker default in the short run. In a similar vein to financial markets, being contrarian is not generally advisable[4].

The limitations of the Brier Score as a metric may have been one reason for not finding evidence of our hypothesis that likely events are predicted more accurately than unlikely events. An outcome predicted to occur 1% but occurring 2% of the time has an expected Brier Score of 0.0197 while an outcome that occurs 95% of the time but with a prediction of 90% has an expected Brier Score of 0.05. The latter is a higher value, even though the former represents a mis-estimation of 100%. An outcome predicted to occur 50% of the time has an expected Brier Score of 0.25. The Brier-Score is a non-linear function. However, this does not invalidate the results obtained as even taking into consideration the non-linearity of the Brier Score, no correlations would have been expected when using this metric. The fact that such correlations show strength in the results, especially when considering that the Brier Score is symmetric around 0.5[5].

It could also be that soccer and other sporting matches are "small worlds," with relatively few potential events which bookmakers can predict accurately compared to more-complex real world events. One test of these contrasting hypotheses is to explore whether bookmakers' predictions of real world events, such as Brexit or Donald Trump's election, are also more accurate for less likely events.

An implication for bookmakers is derived from our supported hypothesis that bettors lose more on events that are more-accurately predicted by bookmakers. The bookmaker profit margin means that bookmakers need not forecast probabilities perfectly in order to achieve expected positive returns (Cortis, 2015). Yet our results indicate that greater accuracy implies higher bookmaking profits. If bookmakers manage to increase their prediction accuracy relative to bettors', perhaps through larger datasets and improvements in machine learning, then bettors' losses may be expected to increase in the future. This observation may be relevant to any policy-makers who are worried about the scale of bettors' losses, of over €6

[4] An example is Tony Dye who was selling off equities in the mid-90s predicting a stock market crash. He was fired just a few days before the market crashed (The Independent,2008).

[5] Predictions of x% likelihood have the same expected Brier Score as predictions of (1-x)% likelihood. For example, the expected Brier Score for a prediction 5% has a Brier Score of 0.0475, the same as the expected Brier Score of a prediction that is 95% likely.

billion in 2015 (European Gambling and Betting Association, 2016). This is in contrast to the traditional economic model, which would predict that increased bookmaker competition (see Figure 1) should lead to lower bettor losses.

Overall our results show that bettors' losses are higher on unlikely events; that unlikely events are better predicted by bookmakers; and that bettors lose more on accurately predicted events. These results should be noted by gambling policymakers, given previously established findings that British bookmakers tend to heavily advertise "complex" unlikely events on TV and in their shop windows (Newall, 2015; Newall, 2017). Complex gambles such as, "Thomas Müller to score the first goal and Germany win 3-1", offer high potential wins despite having far higher bookmaker profit margins than the gambles evaluated in the present study (Newall, 2015; Newall, 2017). Furthermore, these bets tend to involve combinations of likely events, such as a star player scoring the first goal, or a favourite team winning by a specific high scoreline (Newall, 2015). In fact these bets on complex events muddy the historical distinction between favourites and longshots, since greater bet complexity allows them to be simultaneously both (a longshot combined of multiple "likely" events). Research should continue to investigate these issues, in order to help protect soccer bettors' wallets against the risk of increasing bookmaker sophistication.

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Appendix

No odds available:

- 2011/12: Leiria - Nacional as Leira was facing financial difficulties.
- 2009/10: All Mouscron (Belgium) matches as the team was declared bankrupt and Belgian Pro League playoffs.

1X2 odds unavailable:

- 2005/06: Messina - Lazio odds excluded as average odds implied the existence arbitrage as defined by Cortis (2015).

Over/under 2.5 odds unavailable.

- 2005/06: Cagliari – Fiorentina.
- 2006/07: Porto - Leira*, Sporting Lisbon - Boavista*, Beira Mar – Aves, Burnley – Stoke.
- 2008/09: Rangers – Falkirk*, Aberdeen – Celtic*, Kilmarnock – Falkirk*, St Mirren – Motherwell*, Inverness - Hamilton, Lazio – Reggina*.
- 2009/10: Deportivo La Coruna – Valencia excluded as average odds implied the existence arbitrage as defined by Cortis (2015).
- 2011/12: Benfica – Leiria.
- 2013/14: Real Madrid – Villareal as the betting margin was over 300% indicating a possible error.
- 2015/16: Benfica – Uniao Madeira
- 2016/17: Belenenses – Boavista, AZ Alkmaar – Nijmegen, Celtic – Motherwell excluded as average odds implied the existence arbitrage as defined by Cortis (2015).

Match odds unavailable but approximated using Bet365.com odds

- All matches marked *
- 2006/07: Biera Mar – Aves Pacos, Sporting Braga – Ferreira