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Forecasting Football Results and the Efficiency of Fixed-odds Betting

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ABSTRACT
An ordered probit regression model estimated using 10 years' data is used to forecast English league football match results. As well as past match results data, the significance of the match for end-of-season league outcomes, the involvement of the teams in cup competition and the geographical distance between the two teams' home towns all contribute to the forecasting model's performance. The model is used to test the weak-form efficiency of prices in the fixed-odds betting market. A strategy of selecting end-of-season bets with a favourable expected return according to the model appears capable of generating a positive return. Copyright © 2004 John Wiley & Sons, Ltd.

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INTRODUCTION

The predictability of match results is the main concern of research on the efficiency of sports betting markets. In the case of association football (soccer) most previous research has focused on modelling home and away team scores. The recent applied statistics literature has focused primarily on modelling goal scoring (Dixon and Coles, 1997; Rue and Salvesen, 2000; Crowder *et al*., 2002). Recently some econometricians have suggested modelling match results directly (rather than indirectly through scores) using discrete choice regression models (Forrest and Simmons, 2000a,b; Koning, 2000; Kuypers, 2000). An emphasis on match results rather than scores can be justified partly on grounds of simplicity: fewer parameters are required; estimation procedures are simpler; and the resulting models lend themselves to the inclusion of a variety of explanatory variables. This paper presents an explicit forecasting model for football match results based on ordered probit regression. It is the first to quantify the predictive quality not only of past match results data (as in the applied statistics studies cited above), but also of a number of other explanatory variables. The significance of the match for championship, promotion or relegation issues; the involvement of the teams in cup competition; and the geographical distance between the teams' home towns all exert a significant influence on match results, and contribute to the forecasting model's performance.

Research into the efficiency of prices set by bookmakers in betting markets has provided a small but increasing contribution to the literature on the efficiency of financial markets. Much of this

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literature focuses on racetrack betting, but betting on team sports match results has also attracted attention. Early researchers sought evidence of inefficiencies in the form of systematic biases in bookmakers' odds, such as home–away team or favourite–longshot biases. More recently forecasting models have been used to establish whether historical information available in previous match results can be extrapolated to formulate profitable betting strategies. This paper uses the ordered probit match results forecasting model outlined above to test the weak-form efficiency of a prominent high street bookmaker's odds.

The paper is structured as follows. The next section reviews the literature on modelling and forecasting football match results. We then describe the specification and estimation of the ordered probit match results forecasting model. A further section reviews the literature on betting market efficiency, before we investigate the efficiency of the odds quoted by a high street bookmaker during the 1999 and 2000[1] English football seasons, using both regression-based tests and direct economic tests of the profitability of betting strategies based on the forecasting model's evaluation of the expected returns from alternative bets. A final section concludes.

FORECASTING FOOTBALL MATCH RESULTS

A limited but increasing number of academic researchers have attempted to model match results data for football. Early contributions by Moroney (1956) and Reep *et al.* (1971) use the Poisson and negative binomial distributions to model at an aggregate level the distributions of the numbers of goals scored per game. This aggregate approach precludes the generation of specific forecasts for individual matches based on information about the respective strengths of the two teams. By comparing final league placings with experts' pre-season forecasts, however, Hill (1974) demonstrates that individual match results do have a predictable element, and are not determined solely by chance.

Maher (1982) develops a model in which the home and away team scores follow independent Poisson distributions, with means reflecting the attacking and defensive capabilities of the two teams. A full set of attacking parameters and a set of defensive parameters for each team are estimated *ex post* (after observing the full set of match results), but the model does not predict scores or results *ex ante*. A tendency to underestimate the proportion of draws is attributed to interdependence between the home and away scores, and is corrected using the bivariate Poisson distribution to model scores.

Dixon and Coles (1997) employ a similar approach to develop a forecasting model capable of generating *ex ante* match outcome probabilities. The home and away team scores follow independent Poisson distributions, but for low-scoring matches an *ad hoc* adjustment allows for interdependence, increasing the probabilities of 0–0 and 1–1 draws and reducing the probabilities of 1–0 and 0–1 wins. All parameters are estimated using data from previous matches only. Using a similar framework, Rue and Salvesen (2000) assume that the time-varying attacking and defensive parameters of all teams vary randomly over time. Bayesian methods are used to update the prior estimates of these parameters as new match results information is received, and Markov chain Monte Carlo iterative simulation techniques are used for inference. Crowder *et al.* (2002) develop a procedure for updating the team strength parameters that is computationally less demanding.

Several researchers have investigated the impact of specific factors on match results. Barnett and Hilditch (1993), for example, investigate whether artificial playing surfaces, introduced and subse-

[1] For convenience seasons are referred to by their end year, so 1999–2000 is the 2000 season, and so on.

quently abandoned by several clubs during the 1980s and early 1990s, conferred (additional) home-team advantages. Ridder *et al.* (1994) show that player dismissals have a negative effect on the match result from the viewpoint of the team completing the match with fewer than 11 players. Clarke and Norman (1995) use a range of non-parametric techniques to identify the effect of home advantage on match results. Dixon and Robinson (1998) investigate variations in the scoring rates of the home and away teams during the course of a match. The scoring rates at any time depend partly upon the number of minutes elapsed, but also upon which (if either) team is leading at the time.

Recently, several researchers have used discrete choice regression models to model match results directly, rather than indirectly through scores. Apart from its computational simplicity, a major advantage of this approach is its avoidance of the thorny problem of interdependence between the home and away team scores.[2] Forrest and Simmons (2000a,b) investigate the predictive quality of newspaper tipsters' match results forecasts, and the performance of the pools panel in providing hypothetical results for matches that were postponed. Koning (2000) estimates a model to describe a set of match results *ex post*, as part of a broader analysis of changes in competitive balance in Dutch football. Kuypers (2000) uses a variety of explanatory variables drawn from current-season match results to estimate an *ex ante* forecasting model. Audas *et al*. (2002) use a model similar in structure to the one reported below, but with a different sample period and covariates, to examine the impact of managerial change on English football match results data since the 1970s.

AN ORDERED PROBIT MATCH RESULTS FORECASTING MODEL

In this section an ordered probit regression model is developed to forecast the results of professional football matches in England and Wales. The competitive structure is as follows. The top 20 teams compete in the Premier League (PL), and the next 72 teams compete in three 24-team Football League divisions (FLD1 to FLD3). Teams within the PL and within each division of the Football League play each other twice (home and away) each season. At the end of each season, three PL teams are relegated to FLD1 and three FLD1 teams are promoted to the PL. Three teams are promoted/relegated between FLD1 and FLD2; four between FLD2 and FLD3; and one between FLD3 and the top (mostly semi-professional) non-league division. Divisional league tables are compiled by awarding three league points for a win and one for a draw. The football season runs from August to May.

All match results data are obtained from various editions of *Rothmans Football Yearbook*. In the ordered probit model, the result of the match between teams i and j, denoted $y_{i,j}$, depends on the unobserved variable $y^*_{i,j}$ and a normal independent and identically distributed (NIID) disturbance term, $\varepsilon_{i,j}$, as follows:

$$\begin{array}{llll} \text{Home win} & \Rightarrow & y_{i,j} = 1 & \text{if} \quad \mu_2 < y^*_{i,j} + \varepsilon_{i,j} \\ \text{Draw} & \Rightarrow & y_{i,j} = 0.5 & \text{if} \quad \mu_1 < y^*_{i,j} + \varepsilon_{i,j} < \mu_2 \\ \text{Away win} & \Rightarrow & y_{i,j} = 0 & \text{if} \quad y^*_{i,j} + \varepsilon_{i,j} < \mu_1 \end{array} \tag{1}$$

[2] If scores are the focus, the difference between a 0–0 draw and a 1–0 home win is the same as the difference between a 1–0 and a 2–0 home win, or between a 2–0 and a 3–0 home win. If results are the focus, there is a large difference between a 0–0 draw and a 1–0 win, but no difference between home wins of different magnitudes. What is crucial is which (if either) team won; the precise numbers of goals scored and conceded by either team are incidental.

$y^*_{i,j}$ depends on the following systematic influences on the result of the match between teams i and j:

$P^d_{i,y,s} = p^d_{i,y,s}/n_{i,y}$, where $p^d_{i,y,s}$ = home team i's total 'points' score, on a scale of 1 = win, 0.5 = draw, 0 = loss in matches played 0–12 months ($y = 0$) or 12–24 months ($y = 1$) before current match; within the current season ($s = 0$) or previous season ($s = 1$) or two seasons ago ($s = 2$); in team i's current division ($d = 0$) or one ($d = \pm 1$) or two ($d = \pm 2$) divisions above or below the current division; and $n_{i,y}$ = team i's total matches played 0–12 months ($y = 0$) or 12–24 months ($y = 1$) before current match.
$R^H_{i,m}$ = Result (1 = win, 0.5 = draw, 0 = loss) of mth most recent home match played by home team i ($m = 1, \ldots, M$).
$R^A_{i,n}$ = Result of nth most recent away match played by home team i ($n = 1, \ldots, N$).
$\mathrm{SIGH}_{i,j}$ = 1 if match has championship, promotion or relegation significance for home team i but not for away team j; 0 otherwise.
$\mathrm{SIGA}_{i,j}$ = 1 if match has significance for away team j but not for home team i; 0 otherwise.
CUP_i = 1 if home team i is eliminated from the FA Cup; 0 otherwise.[3]
$\mathrm{DIST}_{i,j}$ = natural logarithm of the geographical distance between the grounds of teams i and j.
$P^d_{j,y,s}$, $R^H_{j,n}$, $R^A_{j,m}$, CUP_j = as above, for away team j.

For the purposes of the weak-form efficiency tests reported later, the match results forecasting model is estimated twice: first, using data for the 10 seasons 1989 to 1998 (inclusive) to generate forecasts for the 1999 season; and second, for seasons 1990 to 1999 to generate forecasts for the 2000 season. Since the models for both estimation periods are very similar, Table I reports the 1990 to 1999 model only. In this case there are 19,744 useable match result observations.[4] The contribution to the model of each set of explanatory variables is now considered.

Team quality indicators

The win ratio variables $P^d_{i,y,s}$ (for team i, and their counterparts for team j) are the main team quality indicators. The higher the value of $y^*_{i,j}$ the higher is the probability of a home win, so positive home team and negative away team coefficients are expected. It is assumed that team i's underlying quality is captured by its win ratio over the previous 12 months, $P^0_{i,0,0} + \sum_{d=-1}^{+1} P^d_{i,0,1}$, and its win ratio between 12 and 24 months ago, $\sum_{d=-1}^{+1} P^d_{i,1,1} + \sum_{d=-2}^{+2} P^d_{i,1,2}$. The model allows the individual components of these sums to make different contributions to the team quality measure. For example, if current-season results are a better indicator of current team quality than previous-season results in the same division within the same 12-month period, the coefficient on $P^0_{i,0,0}$ should exceed the coefficient on $P^0_{i,0,1}$. If previous-season results from a higher division indicate higher quality than those from a lower division, the coefficient on $P^{+1}_{i,1,1}$ should exceed the coefficient on $P^0_{i,1,1}$, and so on. Experimentation indicated

[3] The FA Cup is a sudden-death knock-out tournament involving both league and non-league teams. FLD2 and FLD3 teams normally enter the cup in November, followed by PL and FLD1 teams in January. The final is played at the end of the league season, usually in early or mid-May.
[4] The number of useable observations is slightly less than the 20,362 matches completed between the 1990 and 1999 seasons, because full sets of lagged results are unavailable for teams entering (or re-entering) the league during their first two seasons of membership.

Table I. Ordered probit estimation results

1. WIN RATIOS OVER PREVIOUS 24 MONTHS ($P^d_{i,y,s}$, $P^d_{j,y,s}$)

Matches played:	Home team (i)				Away team (j)			
	0–12 months ($y = 0$)		12–24 months ($y = 1$)		0–12 months ($y = 0$)		12–24 months ($y = 1$)	
	Current season ($s = 0$)	Last season ($s = 1$)	Last season ($s = 1$)	Two seasons ago ($s = 2$)	Current season ($s = 0$)	Last season ($s = 1$)	Last season ($s = 1$)	Two seasons ago ($s = 2$)
Two divisions higher ($d = 2$)				0.893 (0.890)				−1.658** (0.888)
One division higher ($d = 1$)		1.603*** (0.292)	0.714*** (0.259)	0.742*** (0.232)		−1.096*** (0.287)	−0.466** (0.259)	−0.790*** (0.230)
Current division ($d = 0$)	1.768*** (0.184)	1.057*** (0.163)	0.640*** (0.160)	0.487*** (0.154)	−1.443*** (0.182)	−0.720*** (0.161)	−0.411*** (0.160)	−0.431*** (0.152)
One division lower ($d = -1$)		0.802*** (0.151)	0.533*** (0.144)	0.491*** (0.133)		−0.492*** (0.152)	−0.288** (0.146)	−0.129 (0.132)
Two divisions lower ($d = -2$)				−0.073 (0.246)				−0.635*** (0.253)

2. MOST RECENT MATCH RESULTS ($R^H_{i,m}$, $R^A_{i,n}$, $R^H_{j,n}$, $R^A_{j,m}$)

Number of matches ago (m,n)	1	2	3	4	5	6	7	8	9
Home team (i)									
Home matches (HH)	0.010 (0.010)	0.006 (0.010)	0.036*** (0.010)	−0.002 (0.010)	0.003 (0.010)	−0.001 (0.010)	0.001 (0.010)	−0.006 (0.010)	0.013* (0.010)
Away matches (HA)	0.003 (0.010)	0.025*** (0.010)	0.020** (0.010)	−0.011 (0.010)					
Away team (j)									
Home matches (AH)	−0.012 (0.010)	−0.013* (0.010)	−0.013* (0.010)	−0.023** (0.010)					
Away matches (AA)	−0.018** (0.010)	−0.006 (0.010)	−0.017* (0.010)	−0.016* (0.010)	0.004 (0.010)	−0.014* (0.010)	−0.009 (0.010)	−0.006 (0.010)	−0.020** (0.010)

3. OTHER EXPLANATORY VARIABLES / 4. CUT-OFF PARAMETERS

	$SIGH_{i,j}$	$SIGA_{i,j}$	CUP_i	CUP_j	$DIST_{i,j}$	$\hat{\mu}_1$	$\hat{\mu}_2$
	0.133*** (0.048)	−0.124*** (0.047)	−0.094*** (0.030)	0.086*** (0.030)	0.052*** (0.010)	−0.218 (0.112)	0.543 (0.112)

5. DIAGNOSTIC TESTS

	Normality	Heteroscedasticity	Omitted lagged variables	
			Win ratios: 24–36 m'ths ($y = 2$)	Results: $m = 10, \ldots, 12$ (HH,AA); $n = 5, \ldots, 6$ (HA,AH) matches ago
	$\chi^2(2) = 0.047$	$\chi^2(1) = 0.011$	$\chi^2(24) = 19.70$	$\chi^2(10) = 9.73$

Notes: Estimation period is seasons 1990 to 1999 (inclusive). Number of observations = 19,744.
Standard errors of estimated coefficients are shown in parentheses.
*** = significant at 1% level (one-tail test); ** = significant at 5% level; * = significant at 10% level.

that the coefficients on $\{P^d_{i,y,s}, P^d_{j,y,s}\}$ were strongly significant for $y = 0,1$; but not for $y = 2$ (defined in the same way as described above for matches that took place 24–36 months prior to the match in question). $\chi^2(20)$ in panel 5 of Table I is Weiss's (1997) omitted variables Lagrange Multiplier (LM) test for the joint significance of the 20 additional coefficients on $\{P^d_{i,2,s}, P^d_{j,2,s}\}$ for $d = -2, \ldots, +2$, $s = 2,3$ (using the scoring form of the information matrix). The test is not significant.

Recent performance indicators

The recent match results variables $R^{H}_{i,m}$ and $R^{A}_{i,n}$ (for team i, and their counterparts for team j) allow for the inclusion of each team's few most recent home and away results in the calculation of $y^*_{i,j}$. Although $R^{H}_{i,m}$ and $R^{A}_{i,n}$ also contribute towards the values of $P^d_{i,y,s}$ and are to some extent correlated with these variables, the possibility of short-term persistence in match results suggests $R^{H}_{i,m}$ and $R^{A}_{i,n}$ may have particular importance (over and above the information they convey about team quality) in helping predict the result of the current match.

Experimentation indicated that the home team's recent home results are more useful as predictors than its recent away results; and similarly the away team's recent away results are more useful than its recent home results. Statistically significant estimated coefficients are obtained for some (but not all) values of $m \leq 9$, and for some $n \leq 4$. $M = 9$ and $N = 4$ are the chosen lag lengths. $\chi^2(10)$ in panel 5 of Table I is the omitted variables LM test statistic (Weiss, 1997) for the joint significance of the 10 additional coefficients on $\{R^{H}_{i,m}, R^{A}_{i,n}, R^{H}_{j,n}, R^{A}_{j,m}\}$ for m = 10,11,12 and n = 5,6. The test is not significant.[5]

Other explanatory variables

The identification of matches with significance for championship, promotion and relegation issues has been an important issue in the literature on the estimation of the demand for match attendance (Jennett, 1984; Peel and Thomas, 1988). It is also relevant in the present context, since match outcomes are likely to be affected by incentives: if a match is significant for one team and insignificant for the other, the incentive difference is likely to influence the result. The algorithm used here to assess whether or not a match is significant is crude but simple. A match is significant if it is still possible (before the match is played) for the team in question to win the championship or be promoted or relegated, assuming that all other teams currently in contention for the same outcome take one point on average from each of their remaining fixtures.[6] Estimated coefficients on $\text{SIGH}_{i,j}$ and $\text{SIGA}_{i,j}$ that are positive and negative (respectively) are consistent with incentive effects of the kind described above. Both coefficients reported in Table I are signed accordingly and significant at the 1% level.

Early elimination from the FA Cup may have implications for a team's results in subsequent league matches in either direction. On the one hand, a team eliminated from the cup may be able to concentrate its efforts on the league, suggesting an improvement in league results. On the other hand, elimination from the cup may cause loss of confidence, suggesting a deterioration in league results. In Table I the estimated coefficient on CUP_i is negative and the coefficient on CUP_j is positive; both are significant at the 1% level. This suggests that the second of the two effects described above

[5] Other similar tests were carried out using various permutations of additional variables for $m > 9$ and $n > 4$, with the same result.

[6] Several alternative definitions of significance were considered, but the chosen algorithm produced values of $\text{SIGH}_{i,j}$ and $\text{SIGA}_{i,j}$ with the most explanatory power in the ordered probit model. The algorithm succeeds in identifying those matches, mostly played during the last few weeks of the season, in which there is a major difference between the incentives facing the teams.

dominates. Contrary to football folklore, elimination from the cup appears to have a harmful effect on the team's subsequent league results.

Finally the estimated coefficient on $\mathrm{DIST}_{i,j}$ is positive and significant at the 1% level. The greater intensity of competition in local derbies may have some effect in offsetting home advantage in such matches, while the difficulties of long-distance travel for the away team and its supporters appear to increase home advantage in matches between teams from opposite ends of the country.

Cut-off parameters and diagnostic tests

Panel 4 of Table I reports the estimated cut-off parameters in (1), $\hat{\mu}_1$ and $\hat{\mu}_2$. In addition to the omitted variables LM tests described above, panel 5 reports Glewwe's (1997) LM test of the normality of $\varepsilon_{i,j}$ in (1) against the alternative that $\varepsilon_{i,j}$ follows some other member of the Pearson family of distributions; and Weiss's (1997) LM test (using the scoring form of the information matrix) of the null hypothesis that $\varepsilon_{i,j}$ in (1) are homoscedastic.[7] The normal and homoscedastic null hypotheses are both accepted at any reasonable significance level, suggesting that the ordered probit model provides a suitable representation of the match results data.

THE EFFICIENCY OF THE FIXED-ODDS BETTING MARKET

This section reviews previous literature on the efficiency of team sports betting markets.[8] North American team sports betting markets operate on a spread betting system, whereby the bookmaker quotes a points spread, reflecting an assessment of the expected points difference between the favourite and the underdog. Once a bet is placed the payoffs are fixed, but the bookmaker can adjust the spread as the time of the match approaches in order to equalize the volume of bets placed on either team. Pankoff (1968) developed the first regression-based test of efficiency in the National Football League (NFL) betting market, by regressing match outcomes (measured by the score differential) on bookmakers' spreads. Intercept and slope coefficients insignificantly different from zero and one respectively suggest that the spread was an unbiased predictor of the match outcome (see below). Gandar *et al.* (1988), however, point out the low power of regression-based tests in

[7] In the normality test, the alternative hypothesis is that $\varepsilon_{i,j}$ follows some other member of the Pearson family of distributions with density function:

$$g(\varepsilon_{i,j}) = \exp(q(\varepsilon_{i,j})) \Big/ \int_{-\infty}^{\infty} \exp(q(t))dt \quad \text{where} \quad q(t) = \int [(c_1 - t)/(c_0 - c_1 t + c_2 t^2)]dt$$

Under $H_0: c_1 = c_2 = 0$ (together with the scaling restriction $c_0 = 1$), $g(\varepsilon_{i,j})$ is the standard normal density function. In the homoscedasticity test, $\varepsilon_{i,j} \sim \mathrm{N}(0,\exp(2\sigma z_{i,j}))$ under the alternative hypothesis of heteroscedasticity of known form. $\varepsilon_{i,j}$ are homoscedastic under $H_0: \sigma = 0$. A convenient choice for $z_{i,j}$ is the uncertainty of match outcome measure $z_{i,j} = \hat{\rho}_{i,j}(1 - \hat{\rho}_{i,j})$ where $\hat{\rho}_{i,j} = 1 - 0.5[\Phi(\hat{\mu}_1 - \hat{y}^*_{i,j}) - \Phi(\hat{\mu}_0 - \hat{y}^*_{i,j})]$ is the 'expected result' on a scale of 0 ('certain' away win) to 1 ('certain' home win). The alternative hypothesis allows the variance of the unsystematic component in the match result to vary directly ($\sigma > 0$) or inversely ($\sigma < 0$) with uncertainty of outcome.

[8] Much of the literature on betting market efficiency focuses on racetrack betting. Early contributions consider the relationship between forecast prices, published in the sporting press on the race-day morning, and starting prices at which bets are settled (Dowie, 1976; Crafts, 1985). Attention has also focused on the phenomenon of longshot bias: an empirical tendency for the expected return at longer odds to be lower than at shorter odds. This could arise if bettors prefer risk (Weitzman, 1965; Ali, 1977); if bettors' subjective probabilities of losing are biased (Henerey, 1985); or if risk averse bettors prefer skewness (Golec and Tamarkin, 1998). Alternatively longshot bias may be a consequence of insiders trading on the basis of private information (Shin, 1991, 1992, 1993; Vaughan Williams and Paton, 1997), or informed traders intervening to exploit profitable betting opportunities created by the actions of uninformed, pleasure bettors (Terrell and Farmer, 1996).

rejecting the null hypothesis of efficiency. They propose a series of alternative economic tests, involving direct evaluation of the returns that would have been earned by implementing technical trading rules, which select bets purely on the basis of the past performance of the teams; and behavioural rules, which select bets in an attempt to exploit certain hypothesized behavioural patterns of the public.[9] Using an NFL data set some behavioural rules are found to be profitable, but technical rules are not.

Golec and Tamarkin (1991) test the efficiency of the spreads posted on the outcomes of NFL and college football matches. For NFL betting they find evidence of inefficiencies favouring bets on home wins and bets on underdogs. No evidence of bias is found in the college football betting spreads. Dare and MacDonald (1996) generalize the empirical methodology for regression-based tests. Several earlier tests were based on specifications that imposed implicit restrictions on the general model. Tests that search only for evidence of home–away team or longshot biases, without recognizing the interdependence between these team characteristics, are liable to produce misleading results.[10]

The prices for bets on the results of English football matches are fixed by the bookmakers several days before the match, and are not adjusted as bets are placed even if new information is received. Bookmakers' odds are in the form: a-to-b home win; c-to-d draw; and e-to-f away win. If b is staked on a home win, the overall payoffs to the bettor are +a (the bookmaker pays the winnings and returns the stake) if the bet wins, and $-b$ (the bookmaker keeps the stake) if the bet loses.[11] These quoted prices can be converted to home win, draw and away win 'probabilities': $\theta^{\mathrm{H}}_{i,j} = b/(a + b)$; $\theta^{\mathrm{D}}_{i,j} = d/(c + d)$; $\theta^{\mathrm{A}}_{i,j} = f/(e + f)$. The sum of these expressions invariably exceeds one, however, because the odds contain a margin to cover the bookmaker's costs and profits. Implicit home win, draw and away win probabilities which sum to one are $\phi^{\mathrm{H}}_{i,j} = \theta^{\mathrm{H}}_{i,j}/(\theta^{\mathrm{H}}_{i,j} + \theta^{\mathrm{D}}_{i,j} + \theta^{\mathrm{A}}_{i,j})$, and likewise for $\phi^{\mathrm{D}}_{i,j}$ and $\phi^{\mathrm{A}}_{i,j}$. The bookmaker's margin is $\lambda_{i,j} = \theta^{\mathrm{H}}_{i,j} + \theta^{\mathrm{D}}_{i,j} + \theta^{\mathrm{A}}_{i,j} - 1$.

Pope and Peel (1989) investigate the efficiency of the prices set by four national high street bookmakers for fixed-odds betting on English football. A simple, though as before not very powerful test of the weak-form efficiency hypothesis is based on regressions of match outcomes against implicit bookmaker's probabilities. Consider the linear probability model:

$$r_{i,j} = \alpha_r + \beta_r \phi^r_{i,j} + u_{i,j} \tag{2}$$

[9] A typical behavioural rule is to back underdogs against favourites in cases where the favourite covered the spread by a large margin the previous week.

[10] In other recent US studies, Badarinathi and Kochman (1996) show that a strategy of betting regularly on underdogs in American football was systematically profitable. Gandar *et al.* (1998) find that the bookmakers' closing prices provided a closer approximation to basketball match outcomes than their opening prices. Price movements before close of trade suggest that informed traders were active and influential. Gandar *et al.* (2001) are sceptical over the existence of systematic biases favouring bets on home teams in baseball and basketball.

[11] Several important changes affecting the UK fixed-odds betting market have taken place during and since the period covered by this study. The UK government abolished betting duty (previously levied at the rate of 10 pence per £1 bet) for bets placed via the Internet in 2000, and for bets placed in the high street in 2001. Until 2000 bookmakers required bettors to place combination bets on at least five matches (for bets on home wins) or three matches (for draws or away wins). This restriction was progressively relaxed, and individual bets on any match are now accepted. The requirement to place combination bets does not affect the expected return on any bet, but it does affect the variance. Presumably in response to these changes, bookmakers have increased their margins slightly (by about 1%) since the end of the period covered by this study. For simplicity, all tests reported in this paper are based on current regulations and ignoring any requirement to pay betting duty.

where $r_{i,j} = 1$ if the result of the match between teams i and j results is r, for r = H (home win), D (draw) or A (away win) and 0 otherwise. In (2) a necessary weak-form efficiency condition is $\{\alpha_r = 0, \beta_r = 1\}$. Since ordinary least squares (OLS) estimation of the linear probability model produces a heteroscedastic error structure, Pope and Peel use weighted least squares (WLS) estimation, using $\hat{r}_{i,j}(1 - \hat{r}_{i,j})$ as weights, where $\hat{r}_{i,j}$ are the fitted values of the dependent variable obtained from (preliminary) estimation of the model using OLS.[12] There is some evidence of departures from $\{\alpha_r = 0, \beta_r = 1\}$. Recently Cain *et al.* (2000) report evidence of longshot bias in the fixed-odds betting market for match results and scores in English football. In comparisons of the estimated fair odds with the bookmaker's actual odds for specific scores, there is some evidence of longshot bias. Direct calculations of average profitability for different categories of bet suggest that bets on strong favourites may offer limited profitable betting opportunities.

In order to interpret the results of such tests as evidence that inefficiencies exist, it is necessary to assume that any biases in the bookmaker's odds are of sufficient duration that they could be detected and exploited by bettors. Furthermore, such tests clearly do not assess the accuracy of the odds in the light of all publicly available information, and therefore provide only a partial test of the weak-form efficiency hypothesis. Recent papers by Dixon and Coles (1997), Rue and Salvesen (2000) and Kuypers (2000) address this limitation, using forecasting models to generate match outcome probabilities, which identify bets that offer the highest expected return according to the model. As seen earlier, Dixon–Coles and Rue–Salvesen develop scores models, while Kuypers uses an (unspecified) results model. All three papers report evidence of weak-form inefficiencies, and suggest that profitable betting strategies may exist. The following section of this paper adds to this evidence using, for the first time, an explicit match results forecasting model, as described previously.

EFFICIENCY OF PRICES IN THE FIXED-ODDS BETTING MARKET: EMPIRICAL RESULTS

In this section, tests are presented for weak-form efficiency in the prices quoted by a prominent high street bookmaker for fixed-odds betting on English league football match results during the 1999 and 2000 seasons. If the forecasting model produces information about the match outcome probabilities that is not already reflected in the odds quoted by the bookmaker, then the odds fail to satisfy standard weak-form efficiency criteria: that all historical information relevant to the assessment of the match outcome probabilities should be reflected in the odds quoted.

A full set of weekend fixed-odds betting coupons was collected throughout the 1999 and 2000 seasons. From a total of 4072 league matches played, the forecasting model is capable of generating predictions for 3890.[13] The bookmaker's weekend coupons provided odds for 3139 of these matches, which constitute the data set for the analysis in this section. Estimated *ex ante* probabilities for the 1571 matches available for the 2000 season are obtained by substituting the full set of covariate values for the home and away teams for each match into the ordered probit model esti-

[12] Alternatively, the model can be estimated as a logit regression, in which case different numerical estimates of the coefficients ρ_1 and ρ_2 are expected.

[13] For the 1999 season, matches involving Macclesfield and Halifax (league entrants at the start of the 1998 and 1999 seasons respectively) were discarded, as the forecasting model requires a full set of match results for a complete two-year period prior to the match in question (see footnote 4). For the 2000 season, matches involving Halifax and Cheltenham (entrants at the start of the 2000 season) were discarded for the same reason.

Table II. Bookmaker's implicit probabilities, and forecast probabilities: descriptive statistics

	Bookmaker				Model				Actual		
	$\phi^{H}_{i,j}$	$\phi^{D}_{i,j}$	$\phi^{A}_{i,j}$	PsL	p^{H}_{ij}	$p^{D}_{i,j}$	$p^{A}_{i,j}$	PsL	H(%)	D(%)	A(%)
Prem	0.446	0.267	0.287	0.366	0.462	0.273	0.265	0.365	0.463	0.286	0.251
	0.134	*0.022*	*0.121*		*0.126*	*0.029*	*0.105*				
Div 1	0.455	0.268	0.277	0.359	0.466	0.275	0.258	0.359	0.461	0.292	0.247
	0.108	*0.016*	*0.099*		*0.109*	*0.025*	*0.088*				
Div 2	0.458	0.268	0.275	0.351	0.470	0.276	0.253	0.351	0.436	0.275	0.289
	0.102	*0.016*	*0.093*		*0.098*	*0.023*	*0.078*				
Div 3	0.457	0.268	0.275	0.348	0.464	0.279	0.256	0.346	0.454	0.267	0.279
	0.095	*0.015*	*0.087*		*0.087*	*0.019*	*0.070*				
Aug–Oct	0.453	0.271	0.276	0.351	0.458	0.281	0.261	0.350	0.461	0.278	0.261
	0.095	*0.012*	*0.088*		*0.081*	*0.017*	*0.067*				
Nov–Dec	0.455	0.270	0.275	0.365	0.466	0.277	0.257	0.363	0.478	0.277	0.245
	0.104	*0.015*	*0.095*		*0.100*	*0.022*	*0.082*				
Jan–Feb	0.450	0.270	0.280	0.354	0.466	0.275	0.259	0.355	0.446	0.291	0.263
	0.111	*0.015*	*0.102*		*0.110*	*0.025*	*0.089*				
Mar–May	0.458	0.260	0.281	0.355	0.476	0.270	0.254	0.355	0.430	0.276	0.295
	0.128	*0.023*	*0.114*		*0.127*	*0.030*	*0.104*				
1999	0.452	0.270	0.279	0.350	0.467	0.277	0.256	0.351	0.445	0.286	0.269
	0.102	*0.015*	*0.093*		*0.100*	*0.023*	*0.081*				
2000	0.457	0.265	0.278	0.361	0.465	0.275	0.260	0.359	0.461	0.274	0.265
	0.117	*0.019*	*0.106*		*0.110*	*0.025*	*0.090*				
All	0.454	0.268	0.278	0.356	0.466	0.276	0.258	0.355	0.453	0.280	0.267
	0.109	*0.017*	*0.100*		*0.105*	*0.024*	*0.086*				

Notes: Data for $\phi^{r}_{i,j}$ and $p^{r}_{i,j}$ (r = H,D,A) are cross-sectional means, with standard deviations in italics.
PsL is Rue and Salvesen's (2000) pseudo-likelihood measure of forecasting accuracy: the geometric mean of the bookmaker's or model's probabilities for the actual results.
H(%), D(%) and A(%) are the actual proportions of home wins, draws and away wins.

mated using data for seasons 1990 to 1999 (inclusive) as reported in Table I, generating a fitted value of $y^{*}_{i,j}$ for the match between home team i and away team j, denoted $\hat{y}^{*}_{i,j}$. The estimated home win, draw and away win probabilities are $p^{H}_{i,j} = 1 - \Phi(\hat{\mu}_2 - \hat{y}^{*}_{i,j})$, $p^{D}_{i,j} = \Phi(\hat{\mu}_2 - \hat{y}^{*}_{i,j}) - \Phi(\hat{\mu}_1 - \hat{y}^{*}_{i,j})$ and $p^{A}_{i,j} = \Phi(\hat{\mu}_1 - \hat{y}^{*}_{i,j})$, where Φ is the standard normal distribution function. Probabilities for the 1568 matches available for the 1999 season are obtained in the same way, using the ordered probit model estimated using data for seasons 1989 to 1998 (not reported in Table I).

Table II summarizes features of the implicit bookmaker's probabilities, the model's estimated match result probabilities, and the match outcomes. When the bookmaker's and the model's probabilities are disaggregated by month and by division, there is little systematic variation in the mean probabilities for each outcome, but the cross-sectional standard deviations of both the bookmaker's and the model's probabilities increase systematically during the course of the season. Evidently it is possible to make a more specific assessment of the probabilities for any individual match (based mainly on the current season's results) towards the end of the season than at the start (when results from previous seasons provide the only guidance). The cross-sectional standard deviations are highest in the PL and lowest in FLD3. This appears to reflect a greater degree of competitive balance in the lower than in the upper divisions of the league.

Overall the forecasting model is effective in replicating the main features of the bookmaker's probabilities. As an overall indicator of forecasting accuracy, Rue and Salvesen (2000) suggest the pseudo-likelihood (PsL) measure calculated as the geometric mean of the probabilities for the observed results. PsL can be calculated using both the bookmaker's and the model's probabilities. As Table II shows, the model outperforms the bookmaker in the 1999 season, while the reverse is true in 2000. In both seasons the difference in forecasting performance appears very small.[14]

Regression-based weak-form efficiency tests

Panel 1 of Table III reports WLS estimates of α_r and β_r in (2) for r = H,D,A. Estimations are carried out using all observations, and using observations for matches played in four parts of the season (August–October; November–December; January–February; and March–May) separately. In the estimations using all observations, $H_0: \alpha_r = 0$; $H_0: \beta_r = 1$; and $H_0: \{\alpha_r, \beta_r\} = \{0,1\}$ are accepted for r = H,D,A, indicating no significant departures from these necessary weak-form efficiency conditions.[15]

The availability of the evaluated probabilities obtained from the forecasting model permits an extension of these conventional regression-based weak-form efficiency tests. If the forecasting model produces no additional relevant information (beyond what is already contained in the bookmaker's prices) an additional term in $(p^r_{i,j} - \phi^r_{i,j})$ should be insignificant when added to the regressions described above. The additional weak-form efficiency conditions are $\gamma_r = 0$ and $\{\alpha_r, \beta_r, \gamma_r\} = \{0,1,0\}$ for r = H,D,A in the linear probability model:

$$r_{i,j} = \alpha_r + \beta_r \phi^r_{i,j} + \gamma_r (p^r_{i,j} - \phi^r_{i,j}) + u_{i,j} \tag{3}$$

Panel 2 of Table III reports the WLS estimation results of (3). In the estimations using all observations, $H_0: \gamma_H = 0$ and $H_0: \gamma_D = 0$ are rejected at the 1% level; and $H_0: \gamma_A = 0$ is rejected at the 5% level. Similarly, $H_0: \{\alpha_r, \beta_r, \gamma_r\} = \{0,1,0\}$ is rejected at the 5% level for r = H,A; and at the 1% level for r = D. This appears to constitute reasonably strong and consistent evidence that the forecasting model does contain additional information that is not impounded into the bookmaker's odds, and that the latter are weak-form inefficient. In the estimations for matches played at different times within the season, $H_0: \gamma_r = 0$ are rejected consistently for matches played in March–May, at the 10% level (for r = D); the 5% level (r = H); and the 1% level (r = A). $H_0: \gamma_D = 0$ is also rejected for November–December. These results suggest that the forecasting model's main advantage over the bookmaker derives from its ability to predict matches played in the closing stages of the season.

Economic weak-form efficiency tests

It is also possible to investigate weak-form efficiency directly, by calculating *ex post* the returns that could have been generated by following various betting strategies. Table IV investigates whether a user of the information provided by the forecasting model would have been able to realize a trading profit. Columns (1)–(3) show the gross average monthly returns on £1 bets placed on the match

[14] For the second half of the 1998 season, Rue and Salvesen's model generates similar PsL measures of 0.357 (for the PL) and 0.372 (for FLD1). Both are slightly higher than the corresponding bookmaker's PsL measures (0.353 and 0.357 respectively).

[15] There are some minor departures from these conditions in the estimations for matches played in November–December (for r = H,D,A) and January–February (for r = D). The duration, magnitude and predictability of these departures, however, do not appear to have been sufficient to have created profitable betting opportunities.

Table III. Weak-form efficiency: regression-based tests

Observations	All 3139	Aug–Oct 1009	Nov–Dec 642	Jan–Feb 650	Mar–May 838
1. TESTS BASED ON $r_{i,j} = \alpha_r + \beta_r\phi^r_{i,j} + u_{i,j}$ for r = H,D,A					
Home wins					
Constant	–0.050	0.050	–0.202***	–0.059	–0.051
	(0.034)	(0.073)	(0.076)	(0.073)	(0.055)
$\phi^H_{i,j}$	1.109	0.906	1.505***	1.126	1.051
	(0.073)	(0.157)	(0.163)	(0.160)	(0.119)
F_1	1.12	0.30	5.86***	0.33	1.64
Draws					
Constant	–0.107	0.248	–0.582**	–0.619**	0.065
	(0.111)	(0.321)	(0.254)	(0.251)	(0.168)
$\phi^D_{i,j}$	1.445	0.114	3.190**	3.376**	0.809
	(0.417)	(1.184)	(0.953)	(0.939)	(0.645)
F_1	1.66	0.42	2.64**	3.54**	0.54
Away wins					
Constant	0.001	0.031	–0.072*	0.026	0.006
	(0.020)	(0.041)	(0.040)	(0.045)	(0.036)
$\phi^A_{i,j}$	0.960	0.831	1.149	0.847	1.028
	(0.075)	(0.151)	(0.156)	(0.163)	(0.129)
F_1	0.99	1.05	3.39**	0.73	0.43
2. TESTS BASED ON $r_{i,j} = \alpha_r + \beta_r\phi^r_{i,j} + \gamma_r(p^r_{i,j} - \phi^r_{i,j}) + u_{i,j}$ for r = H,D,A					
Home wins					
Constant	–0.088**	–0.007	–0.210**	–0.098	–0.092
	(0.036)	(0.086)	(0.082)	(0.076)	(0.056)
$\phi^H_{i,j}$	1.182**	1.027	1.521***	1.187	1.118
	(0.077)	(0.185)	(0.172)	(0.163)	(0.119)
$p^H_{i,j} - \phi^H_{i,j}$	0.416***	0.365	0.111	0.632	0.569**
	(0.158)	(0.284)	(0.366)	(0.417)	(0.285)
F_2	3.20**	0.76	3.96***	1.03	2.59*
Draws					
Constant	–0.118	0.234	–0.660***	–0.551***	0.044
	(0.110)	(0.328)	(0.179)	(0.190)	(0.117)
$\phi^D_{i,j}$	1.447	0.133	3.424***	3.098***	0.843
	(0.413)	(1.202)	(0.682)	(0.722)	(0.642)
$p^D_{i,j} - \phi^D_{i,j}$	1.317***	0.811	1.949**	1.103	1.247*
	(0.427)	(0.987)	(0.918)	(0.935)	(0.711)
F_2	4.22***	0.57	6.72***	4.20**	1.29
Away wins					
Constant	–0.024	–0.009	–0.076*	0.012	–0.017
	(0.021)	(0.051)	(0.044)	(0.046)	(0.035)
$\phi^A_{i,j}$	1.083	0.994	1.169	0.947	1.199
	(0.085)	(0.198)	(0.183)	(0.183)	(0.137)
$p^A_{i,j} - \phi^A_{i,j}$	0.418**	0.354	0.076	0.598	0.867***
	(0.171)	(0.302)	(0.385)	(0.460)	(0.318)
F_2	3.33**	1.15	2.29*	1.13	2.68**

Notes: Standard errors of estimated coefficients are shown in parentheses.
t-tests on individual coefficients are for $H_0: \alpha_r = 0$; $H_0: \beta_r = 1$; and $H_0: \gamma_r = 0$.
F_1 is an F-test for $H_0: \{\alpha_r, \beta_r\} = \{0,1\}$ and F_2 is an F-test for $H_0: \{\alpha_r, \beta_r, \gamma_r\} = \{0,1,0\}$.
*** = significant at 1% level (two-tail test); ** = significant at 5% level; * = significant at 10% level.

Table IV. Weak-form efficiency: economic tests

Bets placed on match outcome with highest expected return			All possible bets ranked in descending order of expected return	
	1999 season	2000 season		1999 & 2000 seasons
(1)	(2)	(3)	(4)	(5)
Aug	0.031	0.015	Top 5%	−0.028
Sept	−0.059	0.057	5–10%	0.008
Oct	0.000	−0.018	10–15%	−0.120
Nov	−0.073	−0.179	15–20%	0.005
Dec	0.035	−0.154	20–25%	−0.054
Jan	−0.038	−0.116	25–30%	−0.083
Feb	−0.083	−0.252	30–50%	−0.054
Mar	0.081	−0.044	50–70%	−0.121
Apr/May	0.080	0.080	70–100%	−0.189
All	0.003	−0.055	All	−0.105

Note: Data are average pre-tax (gross) returns per £1 bet.

outcome for which the model's *ex ante* expected return is the highest. It is assumed that a bet is placed on every match played during the month concerned.

The pattern in the results is similar for both the 1999 and 2000 seasons, and is also consistent with the results shown in Table III. Adopting this strategy for matches played in April and May onwards would have generated a positive gross return of +8% in both seasons. In March 1999 the same strategy would have generated a similar gross return, though in March 2000 a loss would have been realized. Columns (1)–(3) of Table IV also suggest that the information provided by the model may enable a positive gross return to be realized at the start, as well as at the end, of the football season. For both the 1999 and 2000 seasons, the same strategy would have generated gross returns of +3.1% and +1.5% respectively on bets placed in August. A positive return would also have been achieved in September 1999 (September of the 2000 season), but a loss would have been realized in September 1998. In panel 2 of Table III the estimated coefficients on $(p^r_{i,j} - \phi^r_{i,j})$ for r = H,A for August–October are both positive and not far short of being significant at the 10% level.

Columns (4)–(5) of Table IV show the average returns from all 9417 possible bets (three bets on each of 3139 matches). The bets are ranked in descending order of their expected return according to the forecasting model, and grouped into nine bands (starting with the top 5%) as shown in column (4). The bets included in columns (1)–(3) offer the highest expected return for each match and are therefore all considered by the model to represent relatively good value for money. By including all possible bets, columns (4)–(5) provide a better impression of the model's capacity to distinguish between bets representing good or poor value across the board.

Despite the presence of some random variation in the average returns between adjacent groups, it is apparent that the returns in column (5) correlate with the rankings by expected return according to the model. A strategy of selecting only those bets which appear at the upper end of the expected returns distribution does not appear to be consistently profitable, however, even on a gross basis. Overall Table IV suggests that placing bets which the model assesses to be good value at specific times in the season (at the end, and perhaps at the start) represents a better strategy for exploiting inefficiencies in the bookmaker's prices. Conversely it can be inferred that the bookmaker makes better use of the available historical information in formulating odds for matches played in mid-season than for matches played at the start and (especially) at the end of the football season.

CONCLUSION

This paper has reported the estimation of an ordered probit regression model, which has been used to forecast English league football results. This paper is the first to quantify the predictive quality not only of past match results data, but also of a number of other explanatory variables. The significance of the match for championship, promotion or relegation issues; the involvement of the teams in cup competition; and the geographical distance between the teams' home towns are all found to contribute to the forecasting model's performance. The ordered probit model is considerably easier to implement than several of the team scores forecasting models that have been developed recently in the applied statistics literature, but still appears capable of achieving comparable forecasting performance.

The forecasting model has been used to test the weak-form efficiency of the prices quoted by a prominent high street bookmaker for fixed-odds betting on match results during the 1999 and 2000 seasons. Regression-based tests indicate that the forecasting model contains information about match outcomes which is not impounded into the bookmaker's odds. The latter are therefore weak-form inefficient. Evidence of inefficiency is particularly strong for matches played during the final few weeks of the season in April and May. A strategy of betting on the match outcome for which the *ex ante* expected return (calculated from the model's probabilities) is the highest would have generated a positive gross return of around +8% for matches played in April and May in both the 1999 and 2000 seasons.

REFERENCES

Ali MM. 1977. Probability and utility estimates for racetrack bettors. *Journal of Political Economy* **85**: 803–815.
Audas R, Dobson S, Goddard J. 2002. The impact of managerial change on team performance in professional sports. *Journal of Economics and Business* **54**: 633–650.
Badarinathi R, Kochman L. 1996. Football betting and the efficient market hypothesis. *American Economist* **40**: 52–55.
Barnett V, Hilditch S. 1993. The effect of an artificial pitch surface on home team performance in football (soccer). *Journal of the Royal Statistical Society, Ser. A* **156**: 39–50.
Cain M, Law D, Peel D. 2000. The favourite–longshot bias and market efficiency in UK football betting. *Scottish Journal of Political Economy* **47**: 25–36.
Clarke SR, Norman JM. 1995. Home ground advantage of individual clubs in English soccer. *The Statistician* **44**: 509–521.
Crafts NFR. 1985. Some evidence of insider knowledge in horse racing betting in Britain. *Economica* **52**: 295–304.
Crowder M, Dixon M, Ledford A, Robinson M. 2002. Dynamic modelling and prediction of English football league matches for betting. *The Statistician* **51**: 157–168.
Dare WH, MacDonald S. 1996. A generalized model for testing the home and favorite team advantage in point spread markets. *Journal of Financial Economics* **40**: 295–318.
Dixon MJ, Coles SC. 1997. Modelling association football scores and inefficiencies in the football betting market. *Applied Statistics* **46**: 265–280.
Dixon MJ, Robinson ME. 1998. A birth process model for association football matches. *The Statistician* **47**: 523–538.
Dowie J. 1976. On the efficiency and equity of betting markets. *Economica* **43**: 139–150.

Forrest D, Simmons R. 2000a. Forecasting sport: the behaviour and performance of football tipsters. *International Journal of Forecasting* **16**: 317–331.
Forrest D, Simmons R. 2000b. Making up the results: the work of the football pools panel, 1963–1997. *The Statistician* **49**: 253–260.
Gandar JM, Zuber RA, O'Brien T, Russo B. 1988. Testing rationality in the point spread betting market. *Journal of Finance* **43**: 995–1008.
Gandar JM, Dare WH, Brown CR, Zuber RA. 1998. Informed traders and price variations in the betting market for professional basketball games. *Journal of Finance* **53**: 385–401.
Gander JM, Zuber RA, Lamb RP. 2001. The home field advantage revisited: a search for the bias in other sports betting markets. *Journal of Economics and Business* **53**: 439–453.
Glewwe P. 1997. A test of the normality assumption in the ordered probit model. *Econometric Reviews* **16**: 1–19.
Golec J, Tamarkin M. 1991. The degree of inefficiency in the football betting market: statistical tests. *Journal of Financial Economics* **30**: 311–323.
Golec J, Tamarkin M. 1998. Bettors love skewness, not risk, at the horse track. *Journal of Political Economy* **106**: 205–225.
Henerey RJ. 1985. On the average probability of losing bets on horses with given starting price odds. *Journal of the Royal Statistical Society, Ser. A* **148**: 342–349.
Hill ID. 1974. Association football and statistical inference. *Applied Statistics* **23**: 203–208.
Jennett N. 1984. Attendances, uncertainty of outcome and policy in Scottish League Football. *Scottish Journal of Political Economy* **31**: 176–198.
Koning RH. 2000. Balance in competition in Dutch soccer. *The Statistician* **49**: 419–431.
Kuypers T. 2000. Information and efficiency: an empirical study of a fixed odds betting market. *Applied Economics* **32**: 1353–1363.
Maher MJ. 1982. Modelling association football scores. *Statistica Neerlandica* **36**: 109–118.
Moroney MJ. 1956. *Facts from Figures*, 3rd edn. Penguin: London.
Pankoff LD. 1968. Market efficiency and football betting. *Journal of Business* **41**: 203–214.
Peel DA, Thomas D. 1988. Outcome uncertainty and the demand for football. *Scottish Journal of Political Economy* **35**: 242–249.
Pope PF, Peel DA. 1989. Information, prices and efficiency in a fixed-odds betting market. *Economica* **56**: 323–341.
Reep C, Pollard R, Benjamin B. 1971. Skill and chance in ball games. *Journal of the Royal Statistical Society, Ser. A* **131**: 581–585.
Ridder G, Cramer JS, Hopstaken P. 1994. Estimating the effect of a red card in soccer. *Journal of the American Statistical Association* **89**: 1124–1127.
Rue H, Salvesen O. 2000. Prediction and retrospective analysis of soccer matches in a league. *The Statistician* **49**: 399–418.
Shin HS. 1991. Optimal betting odds against insider traders. *Economic Journal* **101**: 1179–1185.
Shin HS. 1992. Prices of state contingent claims with insider traders, and the favourite–longshot bias. *Economic Journal* **102**: 426–435.
Shin HS. 1993. Measuring the incidence of insider trading in a market for state-contingent claims. *Economic Journal* **103**: 1141–1153.
Terrell D, Farmer A. 1996. Optimal betting and efficiency in parimutuel betting markets with information costs. *Economic Journal* **106**: 846–868.
Vaughan Williams L, Paton D. 1997. Why is there a favourite longshot bias in British racetrack betting markets? *Economic Journal* **107**: 150–158.
Weiss AA. 1997. Specification tests in ordered logit and probit models. *Econometric Reviews* **16**: 361–391.
Weitzman M. 1965. Utility analysis and group behaviour: an empirical study, *Journal of Political Economy* **73**: 18–26.

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