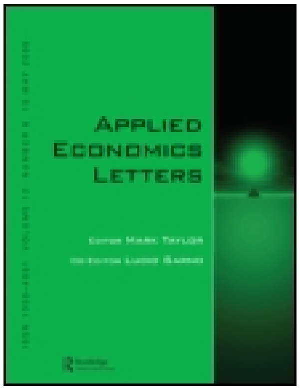

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Herd behaviour and underdogs in the NFL

Sean Wever [a] & David Aadland [a]

[a] Department of Economics and Finance, University of Wyoming, 1000 E. University Avenue, Laramie, WY, 82071, USA

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Herd behaviour and underdogs in the NFL

Sean Wever and David Aadland*

Department of Economics and Finance, University of Wyoming, 1000 E. University Avenue, Laramie, WY 82071, USA

Previous research has failed to draw any clear conclusions about the efficiency of the billion-dollar gambling industry for National Football League (NFL) games. We build on previous research and expose a new market inefficiency, which is consistent with the well-documented notion of *herd behaviour* in behavioural finance. A differential strategy of betting on home and visitor underdogs with large closing lines can produce statistically significant positive returns.

Keywords: market efficiency; herd behaviour; sports betting; NFL

JEL Classification: G14; C25

I. Introduction

We add to an established literature that tests whether National Football League (NFL) betting markets are efficient. Financial economists have a long tradition of testing the efficiency of financial markets (Fama, 1970). Standard economic theory predicts that without frictions or informational failures, markets will be efficient and eliminate all arbitrage opportunities. NFL betting markets and financial markets are similar in several ways: large sums of money are involved, investments are inherently risky and each market is designed to be efficient so abnormally high returns are not available.[1] The existence of profitable betting strategies on NFL games raises doubts about the efficiency of markets in general. Although a few small inefficiencies have been discovered in the NFL betting market, they are generally not robust and a consensus about market efficiency has yet to be reached. Studies such as Zuber *et al.* (1985), Gandar *et al.* (1988), Golec and Tamarkin (1991), Gray and Gray (1997) and Borghesi (2007) find evidence of inefficiencies in the NFL betting market. Conversely, Sauer *et al.* (1988), Dare and MacDonald (1996), and Dare and Holland (2004) find little-to-no evidence of market inefficiency.

We propose a betting strategy that uncovers surprisingly large market inefficiencies in the NFL, implying that the betting line is systematically biased. The strategy is simple. We regress the bet outcome on a dummy variable for home favourites and home underdogs, and their interaction with the closing line. The estimates imply a strategy of only betting on certain underdogs – home teams that are large underdogs and visiting teams that are even larger underdogs. Betting on these select games over the past nine NFL seasons generates out-of-sample winning percentages that are statistically greater than 52.38%, the rate necessary to generate economic profits.[2] In fact, the winning percentages from our preferred betting strategies are in the neighbourhood of 60%. Levitt (2004) and Simmons *et al.* (forthcoming) have also suggested possible biases against underdogs in the NFL betting market.

*Corresponding author. E-mail: aadland@uwyo.edu

[1] In betting markets such as the NFL, the 'odds maker' has the responsibility of setting the price or 'the line' or 'point spread' that produces fair bets. The most popular type of bet for the NFL is a straight bet, which requires the bettor to choose a winner against the point spread.

[2] A bet on either side typically requires \$110 with the chance of winning \$100. This is known as the '11-for-10 rule' or vigorish and is the cost of doing business with the casino. The 11-for-10 rule requires a winning percentage of 52.38% to break even. This break-even percentage can be found by setting the expected value of the bet equal to 0: $10p - 11\,(1 - p) = 0$ and solving for p.

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A common explanation for the apparent irrational behaviour in financial markets is that of *herd behaviour* (Banerjee, 1992; Lux, 1995). Rather than basing investment decisions on rational forecasts of future returns, individuals may instead base their decisions on the actions or words of others. We hypothesize that herd behaviour is responsible for the bias towards favourites in the NFL betting market. The elite teams in the NFL receive excess national attention by pundits, sports analysts and the general press. In response, bettors may tend to overvalue these elite teams, particularly when they are matched up against subpar teams, and place too many bets in their favour. This type of bandwagon effect when applied to the NFL betting market could alternatively be interpreted as an underestimate of the parity in the league.

II. Methodology

In this section, we describe the methods used to test for market efficiency. Previous models (e.g. Gray and Gray, 1997) have identified two possible sources of inefficiency in NFL betting markets: bias towards favourites and visiting teams. Following Borghesi (2007), we specify a probit model that incorporates these biases, as well as the magnitude of the closing line:

$$\begin{aligned} Win^*_{i,s,g} &= \beta_{HF} HF_{i,s,g} + \beta_{HU} HU_{i,s,g} \\ &\quad + \beta_{HFCL}(HF \times CL)_{i,s,g} \\ &\quad + \beta_{HUCL}(HU \times CL)_{i,s,g} + \varepsilon_{i,s,g} \end{aligned} \tag{1}$$

where a positive (negative) value for the latent dependent variable Win^* indicates that the home (visiting) team will win the bet; HF and HU are dummy variables for home team being the favourite or underdog; CL is the closing line; ε is an i.i.d. standard normal error term with cumulative distribution function Φ; and the triplet (i, s, g) indexes team $i = 1, \ldots, I$; season $s = 1, \ldots, S$; and game $g = 1, \ldots, G$.[3] The closing line is calculated as visiting team minus the home team so that negative numbers denote that the home team is favoured.[4]

The efficient market hypothesis (EMH) implies that the closing line will incorporate all available information regarding the outcome of the bet. The EMH implies that

$$\text{EMH}: \beta_{HF} = \beta_{HU} = \beta_{HFCL} = \beta_{HUCL} = 0 \tag{2}$$

The first two restrictions state that, after accounting for the closing line, home favourites and home underdogs do not systematically win bets. The third and fourth restrictions state that the magnitude of the closing line is not correlated with the outcome of the bet. After imposing the EMH, Equation 1 simplifies to $Win^*_{i,s,g} = \varepsilon_{i,s,g}$ or alternatively,

$$p_{i,s,g} = \text{Prob}(Win^*_{i,s,g} > 0) = 0.5 \tag{3}$$

where $p_{i,s,g}$ is the probability that the home team covers the spread. The EMH therefore implies that all betting strategies will produce an expected winning percentage of 50%.

The predicted probability of the home team covering the spread (p) can be used to develop betting strategies. If p exceeds the critical probability p_c, then a bet is placed on the home team.

If instead $p < 1 - p_c$, then a bet is placed on the visiting team. If neither condition is satisfied, no bet is placed. The proportion of winning bets is then compared to 52.38% to test for economic inefficiency. If less than 50 bets are placed, the binomial distribution is used to perform the statistical test and calculate the p-values. If 50 or more bets are placed, the normal approximation to the binomial distribution is used.

III. Data

The data were obtained from www.NFLdata.com and consist of all games from 1985 through 2010. The closing lines are taken from www.VegasInsider.com and measured 12 hours before the beginning of each game. We removed all games played on a neutral site where there is no home or visitor designation, all games where neither team is favoured, all games that finished in a push, and all games in week 17.[5] All overtime games are determined by the final score after the overtime period. The final data set includes 5876 games.

IV. Market Efficiency Results

In this section, we describe the results of our market efficiency tests. First, we use classical testing methods

[3] For our sample period, I ranges from 28 to 32 teams; S represents 24 seasons; and G captures 16 regular season games plus up to three playoff games.
[4] This specification, which essentially estimates separate models for home underdogs and home favourites, addresses the biases highlighted by Dare and MacDonald (1996).
[5] Week 17 is eliminated because teams that have secured a spot in the playoffs will often rest their key players to avoid injury, making it more difficult for odds makers to set efficient lines.

Table 1. Probit estimates

Variable	Mean	Coefficient	SE	p-Value	Marginal effect
Home favourites (HF)	0.6898	0.0828**	0.0389	0.0167	–
Home underdog (HU)	0.3102	0.0659	0.0622	0.1445	–
$HF \times$ Closing line	–4.3128	0.0156***	0.0055	0.0023	0.0062
$HU \times$ Closing line	1.4629	0.0016	0.0134	0.4541	0.0006
LR statistic for EMH		Degrees of freedom			p-Value
8.4624*		4			0.0760

Notes: Table 1 shows the probit estimates for the 1985–1999 NFL seasons, a total of 3259 observations. The marginal effects are calculated at the mean closing lines for HF and HU.
*, ** and ***Significant at the 10%, 5% and 1% levels, respectively.

for the EMH in Equation (2). Using the language from the finance literature, this is a weak test of market efficiency (Fama, 1970). In the second or strong test of the EMH, we develop an out-of-sample betting strategy in an attempt to identify positive economic returns.

Table 1 shows the probit estimates from model (1) during the period 1985 to 1999. The table shows the coefficient estimates and the marginal effects (i.e. the partial derivative in $p_{i,s,g}$ with respect to the closing line for home favourites and home underdogs). The coefficients for HF and the interaction between HF and the closing line are significant. The positive coefficient on the dummy variable ($\hat{\beta}_{HF} = 0.0828$) indicates that, for a small closing line, when the home team is favoured they are more likely to win the bet than when they are underdogs. This contrasts to Gray and Gray (1997) who find a small home-underdog bias for an earlier sample period. The primary difference between our model and previous research is the interaction of home favourites and home underdogs with the closing line, which allows us to expose the differential underdog effect associated with large closing lines. The positive coefficient on the HF–closing line interaction ($\hat{\beta}_{HFCL} = 0.0156$) indicates that an increase in the magnitude of the closing line (a more negative number for home favourites), increases the chance that the visiting team will win the bet. Finally, the likelihood ratio statistic is 8.46 (p-value $=$ 0.076) leading to a rejection of the hypothesis that the NFL betting market is efficient at the 10% significance level.

For the strong test of market efficiency, we use Equation 1 and the probit model to calculate the probability that the home team will cover the spread (p), compare them to various critical probabilities (p_c), count the proportion of bets won and test whether the proportion exceeds the 52.38% threshold for economic efficiency.

Table 2 shows the out-of-sample prediction results for the NFL seasons 2000–2010. When the critical probability (p_c) is 0.5, a bet is placed on all 2617 games. This betting strategy produces a winning percentage of approximately 50% (49.60% to be exact). Obviously, this strategy would lose money and does not show any market inefficiency. However, as the critical probability increases, bets are placed on fewer games and the winning percentages increase.[6] When the critical probability increases to $p_c = 0.53$, the number of games bet falls sharply to two games per week with an approximate winning percentage of 58%. At this level, we find evidence of economic inefficiency at the 5% significance level. The winning percentages at higher critical probabilities are also above 52.38%. However, because of the small samples, they are not all statistically greater than the break-even percentage.

To gain further understanding of the betting strategies implied by the estimates in Table 1, consider solving for the critical closing line from the two following equations:

$$HF\colon \mathrm{Prob}(Win^*_{i,s,g} = 0.0828 + 0.0156 * CL_{i,s,g}) = 1 - p_c \tag{4}$$

$$HU\colon \mathrm{Prob}(Win^*_{i,s,g} = 0.0659 + 0.0016 * CL_{i,s,g}) = p_c \tag{5}$$

Using the standard normal density function, the closing lines that solve Equations (4) and (5) when, for example, $p_c = 0.53$ are -10.5 and $+6.5$, respectively. This implies that the bet should be made exclusively on underdogs – bet on the visiting team when $CL \leq -10.5$ and the home team when $CL \geq 6.5$. Higher critical probabilities imply increasing more restrictive underdog betting strategies.

The lower panel of Table 2 shows the year-by-year prediction results for the betting strategy of $p_c = 0.53$. Between 2000 and 2010, the winning percentages are

[6] We note that the tests of efficiency at different critical probabilities are not independent of one another.

Table 2. Out-of-Sample prediction results

Out-of-sample betting for 2000–2010 based on probit model for 1985–1999

Games bet	Games bet per week	Critical probability	Bets won	Winning percentage (WP)	p-Value (WP > 0.5)	p-Value (WP > 0.5238)
2617	12.52	0.50	1298	49.60	0.6593	0.9978
2149	10.28	0.51	1071	49.84	0.5600	0.9909
1379	6.60	0.52	704	51.05	0.2174	0.8384
427	2.04	0.53	246	57.61	0.0008	0.0152
137	0.66	0.54	80	58.39	0.0247	0.0793

Out-of-sample betting performance by year for a sample strategy ($p > p_c = 0.53$)

Year	Games bet	Critical probability	Bets won	Winning percentage (WP)	p-Value (WP > 0.5)	p-Value (WP > 0.5238)
2000	50	0.53	26	52.00	0.3886	0.5215
2001	35	0.53	23	65.71	0.0448	0.0783
2002	28	0.53	20	71.43	0.0178	0.0322
2003	27	0.53	20	74.07	0.0096	0.0180
2004	28	0.53	15	53.57	0.4253	0.5262
2005	35	0.53	15	42.86	0.8447	0.9028
2006	31	0.53	20	64.52	0.0748	0.1199
2007	48	0.53	27	56.25	0.2354	0.3483
2008	46	0.53	25	54.35	0.3294	0.4534
2009	66	0.53	34	51.52	0.4028	0.5559
2010	33	0.53	21	63.64	0.0814	0.1310

Notes: Table 2 displays the out-of-sample prediction results for the 2000 through 2010 NFL seasons. The coefficients from the probit estimates (1985–1999) are used to form probabilities and bet on NFL games from week 1 through week 20, omitting week 17. If $p > p_c$ then we bet on the home team. If $p < 1 - p_c$ then we bet on the visiting team. Winning percentages that are statistically greater than 50% show statistical inefficiency. Winning percentages that are statistically greater than 52.38% show economic inefficiency. When the games bet are less than or equal to 50, we use the binomial distribution to calculate the p values. For the other cases, we use the normal approximation.

greater than 50% for all but 2005 and greater than 52.38% for all but 2000, 2005 and 2009. The winning percentages are statistically greater than the 52.38% for 2001–2003, 2006 and 2010 at the 15% significance level even considering the small number of games bet each year. This indicates that the inefficiencies are not driven by a single year, but appear to be fairly robust through the decade.

One possible criticism of the previous analysis is that the results from Table 2 may not be robust over a smaller number of games. The out-of-sample results could be driven by a smaller set of games and therefore the inefficiencies may not be a general phenomenon or continue into future years. To investigate this possibility, we repeatedly randomize the games during the period 2000 to 2010 and bet on one-third of the randomized games. Figure 1 shows the distribution of winning percentages over the subset of games. The majority of the distribution is clearly to the right of the 52.38% break-even level with 95% of the subset of games resulting in positive economic returns. Overall,

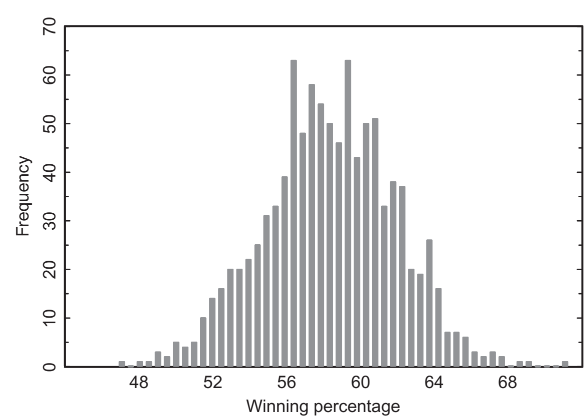

Fig. 1. Frequency distribution of winning percentages

the out-of-sample predictions from 2000 to 2010 indicate that a differential strategy of betting on underdogs with large closing lines will produce winning percentages in the neighbourhood of 60% and statistically significant positive returns.

V. Conclusions

Previous research has failed to draw any clear conclusions about the efficiency of the billion-dollar gambling industry for National Football League (NFL) games. Our results show that a differential strategy of betting on large underdogs can produce statistically significant profitable returns. The evidence from our study suggests that the recent NFL betting market has underpriced large underdogs and bettors have failed to recognize the amount of parity in the NFL. This inefficiency is consistent with a certain amount of herd behaviour towords highly publicized elite teams.

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