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Abstract

Stock markets and betting markets co-exist for professional soccer clubs listed on the London Stock Exchange. For each firm, two pieces of information are released to the stock market on a weekly basis from August to June: experts' expectations about game outcomes through the betting odds, and the game outcomes. Stock markets process the news about games results fast. By contrast, there is no evidence of abnormal returns on the trading days following release of betting information. Moreover, due to the absence of a market reaction to betting odds and the fact that these odds are very good predictors of game outcomes, these odds contain unpriced information and can be used to predict short-run stock returns. Our findings are consistent with theories of under-reaction to public information and the impact of the level of salience of information on the speed at which financial markets process information.

JEL codes: G14, G12, G11.

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Stock price reactions to short-lived public information: the case of betting odds

Abstract

Stock markets and betting markets co-exist for professional soccer clubs listed on the London Stock Exchange. For each firm, two pieces of information are released to the stock market on a weekly basis from August to June: experts' expectations about game outcomes through the betting odds, and the game outcomes. Stock markets process the news about games results fast. By contrast, there is no evidence of abnormal returns on the trading days following release of betting information. Moreover, due to the absence of a market reaction to betting odds and the fact that these odds are very good predictors of game outcomes, these odds contain unpriced information and can be used to predict short-run stock returns. Our findings are consistent with theories of under-reaction to public information and the impact of the level of salience of information on the speed at which financial markets process information.

Introduction

Particular to the UK's corporate landscape is that betting markets and stock markets co-exist for a number of firms: 16 English and 3 Scottish professional soccer clubs are listed on the London Stock Exchange (LSE). For each club, two pieces of information are released on a weekly basis from August to June: the bookmakers' beliefs about the game outcomes through the odds they publish[1], and the game results. The betting system used is a fixed-odds procedure: the odds are posted several days prior to the game and are not altered in response to betting before the event.

Both these types of news provide new information about the performance of the teams/firms: the first type in terms of experts' expectations and the second one in terms of realizations. As a consequence, one would expect that investors track both types of information because they provide useful news about the firms' financial performance. There is a clear and direct relation between the financial performance as measured by the stock returns, and the achievements on the field for the following reasons. First, the proceeds from the national TV deals are redistributed to the teams according to a performance-based scheme, i.e., the end of season ranking (see Falconieri et al. (2004) and Palomino and Sakovics (2004) for details). Second, if a team ends the season ranked among the first four of the top league (the Premier League in England), it has the right to participate to the lucrative European competition (the UEFA Champions' League) during the following season.[2] For teams playing in the First Division (the championship below the Premier League), promotion to the Premier League also brings about a significant increase in income from television rights.[3] Third, field performance has an impact of ticket sales, merchandising and sponsorship revenues.

The objective of this paper is to analyse the market reactions to betting odds and to game results. These two types of news differ in three crucial ways. First, betting odds represent opinions about the probability distribution over the game outcomes. As a consequence, we expect the market reaction to game results to be stronger than the one following the release of betting odds. Second, betting odds offer short-lived information.

[1] See Pope and Peel (1990) for a theoretical model of this system, and Kuypers (2000) and Goddard and Asimakopoulos (2004) for empirical studies. Sauer (1998) wrote a review of the betting literature.
[2] For example, for the season 2000-2001, Manchester United receives national television revenues of Euro 29.29 million and Champions' League participation revenue of Euro 22.2 million. Falconieri et al. (2004) provide more data on television revenues in European soccer.
[3] The sport leagues in Europe operate according to a system of promotion and relegation. Teams ending at the top of their league are promoted to the league ranked immediately above, while teams ending at the bottom are relegated to the league ranking immediately below.

After two trading days, the game outcome is known and the odds' information value has evaporated. As a consequence, if betting odds do contain valuable information, markets must be fast in processing this information. Third, these two types of information also differ in their level of salience. Betting odds are publicly available but are only posted on bookmakers' websites and in 'betting shops'. In contrast, game results are virtually omnipresent: they are extensively discussed in all daily newspapers, on the television news, and in a variety of sports shows on prime time. Therefore, the incorporation of information into the share prices is expected to occur faster in the case of game results.

Our findings are the following. The market processes good news about game results very fast. We observe a positive abnormal return over the first trading day subsequent to the games, but no abnormal return over the second day. Bad news is processed more slowly as we observe a negative abnormal return on both the first and second trading days after a game. In contrast, we cannot find any evidence of a market reaction following the release of betting odds by the bookmakers. These findings are consistent with our assumption of stronger and faster market reaction in the case of game results relative to betting odds. In addition, given that we also find that betting odds are very good predictors of the game outcomes and that there is no market reaction to betting odds, the odds can be used to predict short-run share price returns. Hence, conditional on the reaction to game outcomes, our results suggest that investors under-react to betting odds. As explained by Barberis, Shleifer and Vishny (1998), there is underreaction if 'current good news has power in predicting positive returns in the future'. In this respect, our findings are consistent with the hypothesis of conservatism (Barberis et al. (1998)) or overconfidence in private information (Daniel, Hirshleifer and Subrahmanyam (1998))[4]: when observing betting odds investors do not update their beliefs in a Bayesian way. They seem to put too much weight on their priors. In sum, our results suggest that stock markets process information about realized performances efficiently but disregard some information about future performance.

Our findings are also consistent with the hypothesis that investors' reaction to public news depends on their relative salience: the higher the level of salience, the faster the public information is processed by investors. Information that does not receive large media coverage is incorporated only gradually into the share prices (Klibanoff, Lamont and Wizman (1998))

[4] Another unified theory of over- and underreaction in security markets has been developed by Hong and Stein (1999). Underreaction is based on a gradual release of private information.

Our study differs from previous analyses of the reaction to public news events because we consider a different type of news and a different time horizon.[5] First, the news releases analysed in previous studies are not released with high frequency. For example, earnings releases occur at best on a quarterly basis, mostly even less frequently. By contrast, we study the reaction to news released at high frequency, i.e., on a weekly basis. Second, one type of news (the betting odds) in our study is short-lived. Most recent studies on over- or underreactions to news use time horizons of 6 months to 5 years. After two trading days, our betting odds do not contain further information as the game outcomes are known. One could argue that studying the market reaction to betting odds is somehow equivalent to studying the share price reaction to analyst forecasts. However, we believe that this is different for the following reasons. Bookmakers are not subject to the biases documented about analysts: systematic optimism (Easterbrook and Nutt (1999)) and conflict of interests for analysts working for brokerage firms (Michaely and Womack (1999)). Furthermore, analysts have incentives to herd (see, e.g., Trueman (1994), Welch (2000) and Hong, Kubik and Solomon (2000), Clement and Tse (2004)).

Our paper is also related to the studies by Renneboog and Van Brabant (2000) and Brown and Hartzell (2001) who study the stock price reactions to game outcomes for listed sport clubs. The former study investigates whether share prices of soccer clubs listed on the London Stock Exchange are influenced by the soccer teams' weekly sporty performances. They find a positive abnormal return following wins on the first post-game day, and negative abnormal returns following losses and draws. The abnormal returns for promotion and relegation games are also significantly higher than those of the games played earlier in the season. Brown and Hartzell (2001) study the impact of NBA game results on equity prices of Boston Celtics Limited Partnership. They find that *(i)* the results of the Celtics' basketball games significantly affect partnership share returns, trading volume, and volatility; *(ii)* investors respond asymmetrically to wins and losses, and *(iii)* playoff games have a larger impact on returns than regular-season games.

The organisation of this paper is as follows. Section I discusses the dataset and Section II focuses on methodology. Section III presents the results while Section IV shows some the tests. Finally, Section V concludes.

[5] Daniel, Hirshleifer and Subrahmanyam (1998) review the literature on stock market underreactions in appendix A of their paper.

I. Data description

Currently, 20 UK soccer clubs are listed on the LSE: 12 clubs on the official market and 8 clubs on the Alternative Investment Market (AIM)[6]. In addition, the shares of 4 clubs are traded on OFEX[7], but we do not include these firms in our sample because trading on OFEX is infrequent, is not regulated and there is no guarantee of liquidity. Of the listed clubs, we do not include Watford and Aberdeen as their share price history is too short (due to the fact that their flotations only took place in the final season of our study). We also exclude Leicester City and West Bromwich Albion due to problems with share price data availability. As a result, our dataset covers 16 British soccer clubs listed on the London Stock Exchange. Table I lists our sample clubs, the championship to which they participate (English or Scottish), their league (Premier League, First or Second Division) by season, their rankings at the end of the season, the market on which they are listed (the official market or the AIM), the flotation date, and the market capitalization at the end of the 2002 season. The most valuable clubs are Newcastle United, Chelsea Village and Manchester United.

[Insert Tables I and II about here]

The daily closing share prices of the soccer clubs, their dividends, trading volumes and accounting data as well as the daily returns of the FT All Share index and FTSE All Small index are collected from Thomson Financial Datastream. The turnover and operating performance are exhibited in Table II. Strikingly, virtually all clubs incur operating losses with the notable exception of Manchester United that generated total sales of GBP 146 million with operating earnings of more than GPB 15 million.

The results of each game played by the clubs of Table I during the 3 seasons in the period 1999-2002 were purchased from Mables-Tables, an internet soccer information provider. Our sample does not consist of all the games as those played by two non-listed teams are not taken into account. This is the reason why we do not have the same number of games won and games lost in our sample. Betting odds data are obtained from

[6] The AIM is part of the LSE and designed for small and growing companies. The listing requirements of the AIM are less strict than those of the official market. Over the previous years, 3 clubs were delisted from the AIM: Liverpool at the end of 1995, and Loftus Road (QPR) and Nottingham Forrest, both in December 2001. Therefore, we do not include these clubs into our sample.

[7] OFEX is an unregulated trading facility in which JP Jenkins Ltd. is the main market maker. The following clubs are traded on OFEX : Arsenal, Bradford City, Manchester City and Gillingham.

Ladbrokes, the betting and gaming division of the Hilton Group.[8] The dataset contains betting odds for weekend games (played on Saturday or Sunday, or occasionally on Friday night). These betting data are posted on Ladbrokes' website and betting offices throughout the UK on Wednesday night. In order to avoid contamination of event windows, we exclude those weekend games which are preceded by a Wednesday game.

Those national and international games for which no betting odds are reported (which is exceptional) in the Ladbrokes database are also excluded. Furthermore, in case two listed clubs play against each other, we randomly drop one of the two observations from our sample. The reason is that both the odds and the game results of one team have a mirror image in those of the other team.[9] After matching the stock returns data with the game results and data on betting odds, and after randomly excluding a team in games where both clubs are listed firms, we obtain a final sample of 916 observations.

II. Methodology

A. From betting odds to expectations about game outcomes.

To derive a measure of the predictive power of the betting odds, we proceed as follows. Let *w*, *d* and *l* denote a win, draw and loss, respectively; and let x_{ij} (j=w, d, l) denote the betting odds for a bet on game outcome *j* for team *i*. That is, for one unit of money bet, x_{ij} units of money are awarded to the bettor if outcome *j* is realized for team *i*. Hence, x_{ij}^{-1} represents a measure of the bookmaker's belief about the probability of outcome *j* for team *i*. The normalized probabilities to win and to lose (*ProbWin* and *ProbLoss*) reflect bookmaker's beliefs. These measures are equivalent to the risk-neutral probabilities in the asset pricing literature.

$$ProbWin_i = \frac{x_{iw}^{-1}}{x_{iw}^{-1} + x_{id}^{-1} + x_{il}^{-1}} \qquad (1)$$

$$ProbLoss_i = \frac{x_{il}^{-1}}{x_{iw}^{-1} + x_{id}^{-1} + x_{il}^{-1}} \qquad (2)$$

[8] As the largest and dominant betting bookmaker in the UK, Ladbrokes had turnover of GBP 3.81 billion in 2002.

[9] Expectedly, the results presented throughout the paper would be stronger if this exclusion rule were not implemented.

The denominator in (1) and (2) is known as the over-roundness and determines the gross margin of the bookmakers. It is always higher than 1 such that the bookmakers are expected to realize a profit while incurring minimal risk. Thus, the gamblers have a negative expected return. In our sample, over-roundness has a mean of 1.122 and a standard deviation of 0.005, which signifies that bookmakers will realise a return of 12.2% of the invested (betted) amounts.

We also use a second measure to capture the experts' expectations of the game outcome and their impact on stock returns: the probability difference (*ProbDiff*) of winning and losing games. Thus, game uncertainty is reflected by:

$$ProbDiff_i = ProbWin_i - ProbLoss_i \tag{3}$$

Note that we indirectly include in probability of a draw (which is captured by both $ProbWin_i$ and $ProbLoss_i$). As will be shown later, stock prices react strongly to wins and losses but do not react significantly to draws. The larger *ProbDiff*, the more a win is expected relative to a loss. As *ProbDiff* decreases and approaches 0, the outcome becomes more uncertain. When *ProbDiff* is negative, a loss is more likely to occur a win.

In order to group the games by type of expectations, four dummy variables are constructed by utilizing the above two measures of bookmaker's expectations: *ProbWin* and *ProbDiff*. Each dummy variable is constructed in two ways: specification [a] is based on *ProbWin* and specification [b] is based on *ProbDiff:*

• *SEW (strongly expected to win)*: *SEW[a]* is equal to one if *ProbWin* > 0.45, and zero otherwise. For all these games, we also have *ProbLoss* < 0.28. *SEW[b]* is equal to one if *ProbDiff* > 0.3, and zero otherwise.

• *WEW* (*weakly expected to win*): *WEW[a]* is equal to one if *ProbWin* $\in$ [0.35,0.45], and zero otherwise. For all these games, we also have *ProbWin* > *ProbLoss*. Hence, a win is more likely than a loss. *WEW[b]* is equal to one if *ProbDiff* $\in$ [0,0.3], and zero otherwise.

• *WEL* (*weakly expected to lose*): *WEL[a]* is equal to one if *ProbWin* $\in$ [0.25,0.35], and zero otherwise. For all these games, we have *ProbLoss* > *ProbWin*. Hence, a loss is more likely than a win. *WEL[b]* is equal to one if *ProbDiff* $\in$ [-0.3,0], and zero otherwise.

• *SEL* (*strongly expected to lose*): *SEL[a]* is equal to one if *ProbWin* < 0.25, and zero otherwise. For all these games, we also have *ProbLoss* > 0.48. *SEL[b]* is equal to one if *ProbDiff* < –0.3, and zero otherwise.

These cut-offs are arbitrary and have been chosen so as to have a sufficient number of observations in each sub-sample. Our results remain qualitatively similar when varying the cut-offs points.

B. Abnormal return computation

Denoting $P_{i,t}$ the closing price of stock i on day t, and $\mathrm{Div}_{i,(t-1,t)}$ the dividends paid on stock i over the period $(t-1,t)$, the return of this stock on day t is defined as

$$r_{i,t} = \frac{P_{i,t} - P_{i,t-1} + Div_{i,(t-1,t)}}{P_{i,t-1}} \tag{4}$$

The alternative way of calculating raw returns, $r_{i,t} = ln\,(P_{i,} + Div_{i,(t-1,t)} / P_{i,t-1})$, does not influence the results of this paper. To compute the stocks' abnormal returns, we regress daily returns of each soccer club on the FTSE All Small index, over the full sample period (i.e., Jan. 1, 1999 to Dec. 31, 2002)[10]. We opt for this index to control for the size effect on stock returns.[11]

As some soccer clubs may suffer from non-synchronous trading, we add three leads and three lags of market returns into the market model (See Dimson (1979)). Thus, the market model we consider is

$$r_{i,t} = \alpha_i + \sum_{\tau=-3}^{+3} \beta_{i\tau} r_{m,t+\tau} + \varepsilon_{i,t} \qquad i = 1, \ldots, 16 \tag{5}$$

where $r_{m\tau}$ is the return of FTSE All Small index on day τ. Denoting OLS estimates of α_i and $\beta_{i\tau}$ as a_i and $b_{i\tau}$, respectively, we construct the abnormal return of club i on day t (AR_{it}) as follows[12]:

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[10] Since the events of soccer games take place every week in a season, we cannot use pre-event data as estimation window. Using the full sample period as estimation window, our approach is similar to Brown and Hartzell (2000). Here, abnormal returns are the part of returns that cannot be explained by the covariance between stock returns and market returns.

[11] The results in this paper do no depend upon the choice of the market index. Using the FT All Share index yields similar results.

[12] We also corrected the systematic risk for regression to the mean, but this does not influence the results.

$$AR_{it} = r_{it} - a_i - r_{m,t} \sum_{\tau=-3}^{+3} b_{i\tau} \qquad i = 1, \ldots, 16 \tag{6}$$

Given that there are some periods during the year without weekend games (summer and winter stops), we use two ways to account for event clustering. First, we test the AR significance by the Wilcoxon signed-rank test, which is distribution-free and robust to event clustering. Second, when conducting t-tests, we also control for event clustering by using the standard errors of average abnormal returns for each calendar day (see, e.g. Brown and Warner (1980: 233)).

Given that games are played during the weekend and betting odds are posted on Wednesday evening after the market closes or on Thursday morning, our event window spans a period from Thursday (prior to the game) to Tuesday (subsequent to the game). We take the weekend as the event date and refer to Thursday, Friday, Monday and Tuesday as day -2, -1, 1, and 2, respectively. Therefore, the abnormal return on day -2 (*AR(-2)*) is the abnormal return between Wednesday's closing time and Thursday's closing time as expressed by Equation (6). Similarly, we computed the abnormal returns *AR(z)* with z = -1, 1, 2. The cumulative abnormal return between days z and z', ($z, z' \in \{-2, \ldots, 2\}, z' > z$) is defined as $CAR(z,z') = AR(z) + \ldots + AR(z')$.

III. Results

Our approach to studying the information content of betting odds is structured as follows. First, we examine the price reaction to game outcomes. Second, we investigate the predictive power of betting odds with regard to game outcomes. Finally, we study the price reaction to betting odds.

A. Market efficiency I: Stock price reactions to game results

Panel A of Table III Panel A exhibits the abnormal returns over the two days following the soccer matches which are categorized by the game outcomes (wins, draws and losses) for the entire sample. We observe that the stock prices are sensitive to the information resulting from the game results. A win triggers a positive abnormal return of 53 basis points on day 1 (statistically significant at the 1% level), whereas a loss is followed by a significantly negative return of 57 basis points over the two days following the game. The mean abnormal return subsequent to a draw is negative but not statistically significant. In a three-day event window (not shown), market reactions to game results are even stronger. The CAR(1,3) are 88.26 basis points after a victory, and –100.81 basis points after a defeat, both significant at the 0.1% level. The CAR(1,3) after a draw is –32.54 basis points but not significant. These findings confirm that a win (loss) provides investors with good (bad) news about future cash flows of these listed firms.

A related interesting finding is that the market seems to be faster at processing good news than bad news. Market reactions to a win are concentrated on the first post-game trading day, while price reactions to a loss are realized in both days 1 and 2.

[Insert Table III about here]

We also show that the market reactions to a victory and a defeat are similar in magnitude (Panel A of Table III). Over a two-day window, the difference between reactions (in absolute value) to a win and a loss is insignificant (not reported in the table). This is different from the results obtained in Brown and Hartzell (2001) and Renneboog and Van Brabant (2000) who find that the market reaction to a defeat is stronger than to a victory.

The end-of-season matches may be different in nature from the matches earlier in the season. The reason is that the financial consequences of a victory, a draw or a defeat are more important for teams fighting for promotion to a higher league or for the right to participate in the European championships, or to avoid relegation, as the end of the season draws near. To address this issue, we split our sample in sub-samples. We consider games played in March or earlier in the season, and those played in April or later. The results are presented in Panels B and C or Table III. We find that the results for the August-March sub-sample are similar to those obtained for the entire season (panel A). This implies that the significant market reaction to wins and to losses are not due to large abnormal returns triggered by games played late in the season. Panel C shows that results for the April-June sub-sample are not dissimilar but are somewhat less significant, which may be due to a smaller number of observations.

In a further subsample analysis, we split the April-June sub-sample into four categories based on the teams' end-of-season rankings. The reason is that the financial consequences of the final rankings may differ substantially from category to category, which may be reflected in the share price reactions. The four categories are labelled as follows: *promotion, relegation, top-teams, and other post-March*. *Promotion* games are non-cup[13] games played by teams belonging to the top six in English First or Second League. *Relegation* games are non-cup games played by teams ranked on the fifteenth position or lower in every league. *Top* games are non-cup games played by teams belonging to the top six in English Premier League or top two in Scottish Premier League as they compete for participation in the European championships. Finally, *Other* represent the other non-cup games which were not included in the above categories, but were also played in April, May or June. Panel A of Table IV shows strong statistically significant abnormal returns for the promotion candidates. A victory triggers an abnormal return of 2.13% while a defeat leads to a negative price correction of nearly 2%. The outcomes of the games are quickly incorporated in the share prices (during day 1). The abnormal returns for the relegations candidates (panel B) and the top teams competing for the participation right to European soccer (panel C) are large but lack statistical significance (but sample sizes are tiny).

[Insert Tables IV and V about here]

We also test the market reaction to game results by running regression models including the variables *Win, Loss* and *GoalDiff*. *Win (Loss)* is a dummy equal to one if the team wins (loses) and zero otherwise. *GoalDiff* is the difference between the number of goals scored and those conceded in a game. Hence, it does not only indicate whether or not the team won, lost or obtained a draw, it also captures the magnitude of the victory or the defeat. We estimate the following regressions:

$$CAR(1,2) = \alpha_0 + \alpha_1.Win + \alpha_2.Loss + \beta.ControlVariables + \varepsilon \tag{7}$$

$$CAR(1,2) = \alpha_0 + \alpha_1.GoalDiff + \beta.ControlVariables + \varepsilon \tag{8}$$

where *ControlVariables* include the following dummy variables: *PostMarch* which equals one if a game is played in April, May, or June, and zero otherwise; *AIM* which equals one if the club is listed on the AIM and zero otherwise; *Home* which equals one if the game is a home game and zero in case of an away game; *Cup* which equals one if the game is a national cup game and zero otherwise, two *Year* dummies, and fifteen *Team* dummies. The results presented in Table V confirm that there is a strong positive reaction to a victory. In the first and third regressions, *GoalDiff* is significantly positive at the 0.1%

[13] The cup competitions are different from regular league competitions: all the clubs of the Premier League and Division 1, 2 and 3 can participate in the cup competitions which is a play-off competition with immediate elimination upon defeat.

level, while in the second and fourth regressions, *Win* is significantly positive at the 1% level. In addition, the *PostMarch* dummy is not significant in all regressions, which implies that the significance of our results is not caused by the effect of a limited number of important games played late in the season.

Taken together, Tables III, IV and V confirm that the market react fast to the positive news of a victory as the information is incorporated in the share prices on the first trading day subsequent to the game. The market reaction to a defeat needs 2 days to trickle into the share prices.

B. Can betting odds predict game results?

We also examine whether or not the public information released by specialists (namely, bookmakers) by means of fixed odds is valuable. In other words, we want to know whether betting odds on soccer games have some predictive power. Betting odds are translated into probabilities to win or lose as explained in section II.B. Hence, we estimate the following regressions with *GoalDiff*, *Win* and *Loss* as dependent variables for each type of model:

$$Dep.\ Variable = \alpha_0 + \alpha_1 ProbWin + \beta ControlVariables + \varepsilon \quad (9)$$

$$Dep.\ Variable = \alpha_0 + \alpha_1 SEW[a] + \alpha_2 WEL[a] + \alpha_3 SEL[a] + \beta ControlVariables + \varepsilon \quad (10)$$

$$Dep.\ Variable = \alpha_0 + \alpha_1 ProbDiff + \beta ControlVariables + \varepsilon \quad (11)$$

$$Dep.\ Variable = \alpha_0 + \alpha_1 SEW[b] + \alpha_2 WEL[b] + \alpha_3 SEL[b] + \beta ControlVariables + \varepsilon \quad (12)$$

The models with *GoalDiff* as the dependent variable are estimated using an ordered probit model (where the constant terms are normalized to zero). Those with *Win* or *Loss* as dependent variables are estimated with binary probit models.

[Insert Table VI about here]

Both panels A and B of Table VI show that there is a very strong relation between the game results and the betting odds. The clubs with a high (ex ante) probability to win (*ProbWin*), a high probability difference (*ProbDiff*) and the teams which are strong expected to win (*SEW*), do indeed win their games (models 1, 2, 4 and 5) and are able to avoid defeats (models 4 and 6). Likewise, the teams of which the betting odds strongly predict a defeat (*SEL*) are indeed frequently defeated (as reflected by the positively coefficients in models 4 and 6) and rarely win (as indicated by the negative coefficients in models 1, 2, 4 and 5). It should be noted that all these results are highly statistically significant within the 0.1% level.

Panel A of Table VI also shows that when the betting odds are less clearly predicting a defeat (or a victory) as measured by the variable *WEL[a]* (weakly expected to lose), there is no significant relation between *WEL[a]* and the game results (*GoalDiff, Win, Loss*). When we calculate the 'weakly expected to lose' variable (*WEL[b]*) using the somewhat more refined method of probability differences, we find that teams that are weakly expected lose, do indeed incur more defeats and realise fewer victories (Panel B). Still, the parameter coefficients as well as the statistical significance is lower than for the cases which are strongly predicting victories or defeats. Thus, a higher degree of uncertainty in the betting odds does indeed reflect the higher uncertainty on the field.

To conclude, we can state that betting odds are very good predictors of game outcomes. Our results are consistent with the existing literature on betting market efficiency (see Sauer (1998) for a review).

C. Market efficiency II: Stock price reactions to the release of betting odds

Given that (i) stock prices react strongly to game results and (ii) betting odds are good predictors of these results, one would expect that stock prices react to the announcement of betting odds. If markets are efficient, the above should be fulfilled according to Bayes' rule. Table VII exhibits the mean (cumulative) abnormal returns on the two days prior to the game (Thursday and Friday). Somewhat surprisingly, we find neither an economic nor statistically significant price reaction to the posting of betting odds.

We test the market reaction further by regressing *CAR(-2,-1)* on the predictions from the betting odds (*SEW, WEL, SEL*) and on our standard control variables, and exhibit the results in Table VIII. We observe that none of the estimated coefficients of these expectation dummies is significantly different from zero. This result is consistent with our earlier finding that investors do not react to betting odds to update their beliefs. Again, in the light of the fact that when bookmakers make strong predictions in their betting odds the game results are accurately forecast, it is surprising that the market seems to ignore this information.

[Insert Tables VII and VIII about here]

There are two mutually exclusive explanations for this result. The first explanation is that betting odds do not contain any new information that has not been incorporated into prices. The second explanation is that investors underreact to information conveyed by the betting odds. To find out which of the two explanations prevails, we investigate whether or not betting odds have predictive power for future stock returns. If the odds do predict short-run returns, it follows that the market underreacts to the information in the odds. Indeed, as explained by Barberis, Shleifer and Vishny (1998), there is underreaction if 'current good news has power in predicting positive returns in the future'. Formally, to test the predictive power of odds for stock returns, we compute the average *AR(1), AR(2),* and *CAR(1,2)* conditional on the strength of the bookmakers' prediction as reflected in the betting odds (*SEL, WEL, WEW, SEW*). The results of Table IX show – using either specification (based on the probability to win and on the probability difference) – that if teams are strongly expected to win the abnormal returns *AR(1)* (and *CAR(1,2)*) are significantly positive. This implies that if the betting odds point out that some teams have a very high probability to win their game, the purchase of an equity stake in these listed soccer firms will lead to abnormal returns of almost 29 basis points.

[Insert Tables IX and X about here]

To test this relation between the prediction of the game results by the betting odds and the market price reaction subsequent to the game, we run the following OLS regressions, whereby the control variables are defined above:

$$CAR(1,2) = \alpha_0 + \alpha_1 SEW[i] + \alpha_2 WEL[i] + \alpha_3 SEL[i] + \beta ControlVariables + \varepsilon,\ i=a,b \quad (13)$$

Table X confirms the results of Table IX: when a team is strongly expected to win (*SEW[a]* and *SEW[b]*), we find a statistically significant relation with the CAR(1,2) within the 5% level. Thus, strong expectations to win announce positive abnormal returns immediately after the game. This implies that betting odds can predict short-run returns. Hence, we conclude that the lack of market reaction to betting odds is driven by under-reaction to information about future performance.

Taken together, the results of Sections III.A and III.C show that the market reaction to public information strongly depends on the type of news released. There are two possible explanations for this phenomenon. The first explanation is overconfidence in private information (see, e.g., Daniel, Hirshleifer and Subrahmanyam (1998)). When receiving public information, agents do not update their beliefs in a Bayesian fashion. They put too much weight on their priors and too less weight on the information that is just released. The second explanation for our results regards the differences of media coverage (salience) on betting odds and game results. Game results are available on a large scale: they are presented in all daily newspapers and in various TV programs. Conversely, betting odds are available only on bookmakers' websites or offices. In this respect, our results are consistent with those of Klibanoff, Lamont and Wizman (1998).

IV. Robustness of the findings

A. Transaction costs

We also examine whether the difference in price reactions to betting odds and game outcomes is due to transaction costs. We do not believe that this is the case for the following reasons. First, the expected *CAR(1,2)* following a strong expectation to win by the bookmaker (under both specifications *a* and *b*), and the realized *CAR(1,2)* after a win are not statistically different. This implies that the absence of an investment decision based on betting odds is not due to transaction costs. Second, the results are not induced by (lack of) trading activity. For the stocks in our sample, trading volumes on Friday and Thursday are, respectively, 25% and 16% *larger* than on Monday. Conversely, trading volumes on Tuesday and Wednesday are respectively, 2% and 18% *smaller* than on Monday. Note that the differences are not statistically significant. This rejects the lack of liquidity as a possible explanation for the difference in market reaction to betting odds and to game results.

B. Construction of the prediction variables from betting odds

We also investigate whether our results depend on the way we construct the prediction variables *SEW*, *SEL*, *WEW*, and *WEL*. We find that this is not the case. As already mentioned in Section II.B, our results remain qualitatively equivalent when choosing other thresholds for *ProbWin* and *ProbDiff* to define the dummy variables *SEW*, *SEL*, *WEW*, and *WEL*. For Specification *a*, the alternative sets of thresholds we tested, are: {0.2, 0.3, 0.4} and {0.3, 0.4, 0.5}. For Specification *b*, our alternatives ({-0.2, 0, 0.2}, {-0.25,0,0.25} and {-0.4,0, 0.4}) also yield results similar to the ones presented above.

C. Team media coverage

We also verify that our results are not driven by a few teams that benefit from large media coverage. First, we exclude Manchester United, the most famous (and valuable) soccer team in the UK. Our results remain unchanged. Second, in all regressions, we control for team-specific effects by using team dummies. Third, we divide the teams into two groups based on media coverage. The first group contains eight teams that are more intensely followed by the media: Aston Villa, Chelsea Village, Celtic, Leeds United, Manchester United, Newcastle United, Sunderland and Tottenham Hotspur. The second group comprises the other eight teams. The categorization of the teams in to the two groups with high versus low media coverage is performed using the Factiva database. Factiva, a Dow Jones & Reuters company, is an online information provider that provides access to nearly 9,000 news sources, including local, national and international newspapers, leading business magazines, trade publications, and newswires. To examine the media coverage of the listed soccer clubs, we used club names as key words and searched in news headlines in Factiva.com. We restrict news language to English, and exclude republishing news and recurring pricing and market news. We conclude that the market reaction to betting odds and games results are not significantly different for the two groups of soccer teams. Fourth, media attention may go up near the end of the season when the competition become more exciting. We control for this by using a PostMarch dummy in all regressions. Our results remain unchanged when using post-February or post-April games as end-of-season games.

V. Conclusion

In this paper we have studied the stock price reactions of listed soccer clubs to two types of public information: betting odds which incorporate information about the expected future performance, and game results which capture information about the realized performance. This study differs from previous papers on the stock price reaction to public news in the type of news released. First, the two types of news we consider are correlated in the sense that betting odds comprise a probability distribution over possible game outcomes. Second, these news releases occur at a relatively high frequency compared to the news considered in other studies. Third, betting odds are short-lived information since game outcomes are known shortly (two trading days) after odds are posted.

We have found that the markets are very fast in processing good news about game outcomes (victories) and somewhat slower in incorporating bad news (defeats) in the share prices. The market reactions are strongly statistically significant. In contrast, we do not find significant abnormal returns on trading days following the release of odds by bookmakers. This is surprising as the betting odds are excellent predictors of the game outcomes. Interestingly, due to the absence of a market reaction to the disclosure of betting odds, these odds can be used to predict short-run market returns. This suggests that while markets efficiently process information about the realized performance, they underreact to information comprising expectations. Our findings about the underreaction to betting odds are consistent with conservatism of or overconfidence by investors. Upon receiving public information, they do not seem to update their beliefs in a Bayesian way: they put too much weight on their priors and too less weight on the information that is just released. Our results are also congruent with the salience theory relating speed of information processing with media coverage since information about game results is disclosed on a much larger scale than betting odds.

References

Barberis, N., A. Shleifer, and R. Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307-343.

Brown, G. and J. Hartzell, 2001, Market reaction to public information: The atypical case of the Boston Celtics, *Journal of Financial Economics* 60, 333-370.

Brown, S., and J. Warner, 1980, Measuring security price performance, *Journal of Financial Economics* 8, 205-258.

Clement, M., and, S. Tse, 2004, Financial analysts characteristics and herding behaviour in forecasting, mimeo, University of Texas at Austin.

Daniel, K., D. Hirshleifer, A., Subrahmanyam, 1998, Investor psychology and security market under- and overreaction, *Journal of Finance* 53, 1839-1885.

Dimson, E., 1979, Risk measures when shares are subject to infrequent trading, *Journal of Financial Economics* 7, 197-226.

Easterbrook, J., and S., Nutt, 1999, Inefficiency in analysts' earnings forecasts: systematic misreaction or systematic optimism, *Journal of Finance* 54, 1777-1797.

Falconieri, S., F., Palomino, and J. Sakovics, 2004, Collective vs Individual Sale of TV Rights in League Sports, *Journal of the European Economic Association*, forthcoming.

Goddard, J., and, I., Asimakopoulos, 2004, Forecasting football results and the efficiency of fixed-odds betting, *Journal of Forecasting* 23, 51-66.

Hong, H. and J. Stein, 1999, A unified theory of underreaction, momentum trading, and overreaction in asset markets, *Journal of Finance,* 54, 2143-2184.

Hong, H., J., Kubik, and, A., Solomon, 2000, Security analysts' career concerns and herding of earnings forecasts, *Rand Journal of Economics* 31, 121-144.

Klibanoff, P., O. Lamont, and T. Wizman, 1998, Investor reaction to salient news in Closed-end Country funds, *Journal of Finance* 53, 673-699.

Kuypers, T., 2000, Information and efficiency: An empirical study of a fixed odds betting market, *Applied Economics* 32, 1353-1363.

Michaely, R., and K., Womack, 1999, Conflict of interests and the credibility of underwriter analyst recommendations, *Review of Financial Studies* 12, 653-686.

Palomino, F., and J. Sakovics, 2004, Inter-league competition for talent vs. competitive balance, *International Journal of Industrial Organization* 22, 783-797.

Pope, P., and D., Peel, 1990, Information, prices and efficiency in a fixed-odds betting market, *Economica* 56, 323-341.

Renneboog, L., and P. Van Brabant, 2000, Share price reactions to sporty performances of soccer clubs listed on the London Stock Exchange and the AIM, *CentER DP 2000-19*, University of Tilburg.

Sauer, R., 1998, The economics of wagering markets, *Journal of Economic Literature* 36, 2021-2064.

Trueman, B., 1994, Analysts forecasts and herding behavior, *Review of Financial Studies* 7, 97-124.

Welch, I., 2000, Herding among security analysts, *Journal of Financial Economics* 58, 369-396.

Table I
Soccer clubs and sporty performance

This table presents the soccer clubs in our sample and gives the positions in their affiliated leagues from seasons 1999-2000 to 2001-2002. LSE represents a listing on the London Stock Exchange. AIM stands for the Alternative Investment Market (a segment of LSE). MV is market value in June 2002, in GBP billion. EP (SP) stands for English (Scottish) Premier League. E1 (E2) stands for English First (Second) Division. The numbers next to their league are the rankings at the end of the season in 2002.

Club	List Date	Exchange	MV GBP (billion)	League & Position					
				1999-00		2000-01		2001-02	
Aston Villa	April 1997	LSE	15.2	EP	6	EP	8	EP	8
Burnden Leasure (Bolton Wanderers)	April 1997	AIM	5.1	E1	6	E1	3	EP	16
Birmingham City	March 1997	AIM	13.2	E1	5	E1	5	E1	5
Chelsea Village	March 1996	AIM	31.4	EP	5	EP	6	EP	6
Celtic	Sept. 1995	LSE	15.1	SP	2	SP	1	SP	1
Charlton Athletic	March 1997	AIM	7.7	E1	1	EP	9	EP	14
Heart of Midlothian	May 1997	LSE	7.9	SP	3	SP	5	SP	6
Leeds United	Aug. 1996	LSE	20	EP	3	EP	4	EP	5
Manchester United	June 1991	LSE	27	EP	1	EP	1	EP	3
Millwall	Jan. 1989	LSE	11.4	E2	5	E2	1	E1	4
Newcastle United	April 1997	LSE	31.2	EP	11	EP	11	EP	4
Preston North End	Jan. 1995	AIM	4	E2	1	E1	4	E1	8
Southampton	Jan. 1997	LSE	11.5	EP	15	EP	10	EP	11
Sunderland	Dec. 1996	LSE	18	EP	7	EP	7	EP	17
Sheffield United	Dec. 1996	LSE	2.5	E1	16	E1	10	E1	13
Tottenham Hotspur	Jan. 1983	LSE	29.5	EP	10	EP	12	EP	9

Table II
Operating performance of listed soccer clubs

This table presents the total sales and operating profits (in million GBP) of the listed soccer clubs. The percentages of total sales derived from soccer related activities are reported for 2002. Source: Datastream.

Club	Total Sales				Operating Profit		
	2000	2001	2002		2000	2001	2002
Aston Villa	35.8	39.4	46.7	100%	-5.2	-6.9	-9.9
Burnden Leasure (Bolton Wanderers)	13.4	14.5	36.8	83%	-8.6	-12.8	0.8
Birmingham City	9.4	13.3	15.2	100%	-3.9	-2.6	-6.1
Chelsea Village	106.8	93.6	115.3	64%	2.1	-6.8	-7.7
Celtic	38.6	42	56.9	82%	-5.1	-9.4	-2
Charlton Athletic	11.7	28.3	30.6	100%	-6.7	-0.2	-12.8
Heart of Midlothian	7.1	7.9	6.1	100%	-3.3	-3.7	-3.5
Leeds United	57.1	86.3	81.5	100%	-2.9	-5.7	-28.5
Manchester United	116	129.6	146.1	100%	15.5	19.3	15.2
Millwall	4.8	4.8	10.6	100%	-2.6	-2.6	-0.1
Newcastle United	45.1	54.9	70.9	100%	-19.3	-5.2	0
Preston North End	5.7	7.2	9.9	100%	-1.5	-0.8	0.2
Southampton	20.8	29.1	38.5	81%	-3.4	-2.3	-1.6
Sunderland	37.3	46	43.8	100%	-6.9	1.6	-7.8
Sheffield United	5.8	6.5	10	97%	-5	-3.6	-2.4
Tottenham Hotspur	48	48.4	65	100%	-4.2	-1.7	-4.8
Mean	41.9	43.9	55.9	92%	-4.7	-4.3	-7.4
St. Dev	8.6	6.4	12.9	11%	0.7	3.7	3.6
Median	28.3	34.3	41.2	100%	-4.1	-3.1	-3

Table III
Market reactions to game results

This table presents the average (cumulative) abnormal returns ((C)ARs) in basis points subsequent to the soccer games. Panel B and Panel C show the (C)ARs for the sub-samples of the August-March games and the April-June ones, respectively. The p-values (in parentheses) of the t-test and the Wilcoxon signed-rank test are presented in the first and second rows following the ARs, respectively.

	N	Reaction to games		
		AR(1)	AR(2)	CAR(1,2)
Panel A:	*All games*			
Win	405	52.72	10.73	63.45
p-value of t-test		(0.000)	(0.267)	(0.000)
p-value Wilcoxon		(0.000)	(0.011)	(0.000)
Draw	233	-8.15	-16.87	-25.01
p-value of t-test		(0.652)	(0.304)	(0.367)
p-value Wilcoxon		(0.337)	(0.840)	(0.457)
Loss	278	-27.95	-29.07	-57.02
p-value of t-test		(0.011)	(0.015)	(0.000)
p-value Wilcoxon		(0.095)	(0.008)	(0.003)
Panel B:	*Games in August-March*			
Win	329	51.46	13.70	65.16
p-value of t-test		(0.001)	(0.193)	(0.000)
p-value Wilcoxon		(0.000)	(0.013)	(0.000)
Draw	187	-0.64	-9.18	-9.82
p-value of t-test		(0.974)	(0.620)	(0.748)
p-value Wilcoxon		(0.436)	(0.537)	(0.497)
Loss	222	-21.10	-33.12	-54.22
p-value of t-test		(0.063)	(0.023)	(0.003)
p-value Wilcoxon		(0.163)	(0.021)	(0.006)
Panel C:	*Games in April-June*			
Win	76	58.17	-2.15	56.02
p-value of t-test		(0.051)	(0.929)	(0.186)
p-value Wilcoxon		(0.222)	(0.485)	(0.175)
Draw	46	-38.68	-48.10	-86.78
p-value of t-test		(0.381)	(0.178)	(0.187)
p-value Wilcoxon		(0.544)	(0.397)	(0.714)
Loss	56	-55.10	-13.01	-68.11
p-value of t-test		(0.081)	(0.332)	(0.052)
p-value Wilcoxon		(0.344)	(0.237)	(0.154)

Table IV
Market reactions to April-June games

This table presents average (cumulative) abnormal returns ((C)ARs) in basis points subsequent to the soccer games, for the games played in April-June only. The p-values (in parentheses) of the t-test and the Wilcoxon signed-rank test are presented in the first and second row following the ARs, respectively.

	N	Reaction to games			N	Reaction to games		
		AR(1)	AR(2)	CAR(1,2)		AR(1)	AR(2)	CAR(1,2)
Panel A: Promotion					*Panel B: Relegation*			
Win	17	213.91	-58.97	154.94	3	48.97	1.8608	50.83
p-value of t-test		(0.052)	(0.440)	(0.312)		(0.410)	(0.891)	(0.457)
p-value Wilcoxon		(0.124)	(0.758)	(0.163)		(0.209)	(0.593)	(0.285)
Draw	13	7.31	-209.00	-201.69	6	-213.59	25.05	-188.53
p-value of t-test		(0.949)	(0.093)	(0.340)		(0.383)	(0.146)	(0.444)
p-value Wilcoxon		(0.553)	(0.007)	(0.507)		(0.463)	(0.116)	(0.345)
Loss	9	-191.93	-30.85	-222.78	7	-126.58	8.04	-118.54
p-value of t-test		(0.010)	(0.133)	(0.013)		(0.253)	(0.354)	(0.277)
p-value Wilcoxon		(0.021)	(0.051)	(0.021)		(0.735)	(1.000)	(0.311)
Panel C: Top					*Panel D: Other PostMarch*			
Win	23	12.65	4.05	16.70	33	19.41	22.77	42.18
p-value of t-test		(0.643)	(0.917)	(0.744)		(0.559)	(0.452)	(0.393)
p-value Wilcoxon		(0.976)	(0.584)	(0.927)		(0.131)	(0.339)	(0.313)
Draw	6	-47.95	40.22	-7.73	21	-14.53	5.36	-9.16
p-value of t-test		(0.109)	(0.115)	(0.834)		(0.548)	(0.327)	(0.717)
p-value Wilcoxon		(0.075)	(0.116)	(0.917)		(0.205)	(0.821)	(0.498)
Loss	9	-125.53	-9.96	-135.48	31	-21.21	13.46	-7.74
p-value of t-test		(0.181)	(0.865)	(0.197)		(0.582)	(0.445)	(0.860)
p-value Wilcoxon		(0.260)	(0.678)	(0.441)		(0.176)	(0.318)	(0.248)

Table V
Market reactions to game results: regression results

This table presents the OLS regression results explaining the cumulative abnormal returns (CARs) following soccer games. The dependent variables are CAR(1,2). *Win (Loss)* is a dummy equal to one if the team wins (loses) and zero otherwise. *GoalDiff* is the difference between the number of goals scored and those conceded in a game. *PostMarch* is equal to one if a game is played in April, May, or June, and zero otherwise; *AIM is* equal to one if the club is listed on the AIM and zero otherwise; *Home* is equal to one if the game is a home game and zero in case of an away game; *Cup* is equal to one if the game is a national cup game and zero otherwise. The p-values of the estimated coefficients are in parentheses. All regressions have 916 observations.

Dep. Variable :	AR(1)	AR(1)	CAR(1,2)	CAR(1,2)
Constant	23.40	4.46	-7.35	-22.50
	(0.924)	(0.986)	(0.983)	(0.948)
GoalDiff	18.91		26.22	
	(0.000)		(0.000)	
Win		58.94		83.16
		(0.004)		(0.004)
Loss		-19.20		-35.08
		(0.388)		(0.254)
PostMarch	-16.28	-16.98	-29.21	-29.89
	(0.432)	(0.412)	(0.309)	(0.297)
AIM	-29.06	-29.03	-53.35	-60.95
	(0.907)	(0.907)	(0.876)	(0.859)
Home	-5.77	-4.28	0.77	0.95
	(0.730)	(0.797)	(0.974)	(0.967)
Cup	-18.06	-18.54	6.19	5.87
	(0.536)	(0.526)	(0.878)	(0.885)
Year9900	20.18	19.02	59.03	56.63
	(0.321)	(0.350)	(0.037)	(0.045)
Year0001	27.79	26.11	57.37	54.56
	(0.174)	(0.202)	(0.043)	(0.054)
Team Dummies	Yes	Yes	Yes	Yes
R^2	0.0437	0.045	0.045	0.049
F-Statistics	1.85	1.83	1.91	2.00
Prob > F	0.010	0.010	0.007	0.004

Table VI
Quality of odds

This table presents the estimation results of regressions testing the predictive power of betting odds. *Win (Loss)* is a dummy equal to one if the team wins (loses) and zero otherwise. *GoalDiff* is the difference between the number of goals scored and those conceded in a game. The probabilities to win and to lose (in %) are represented by *ProbWin* and *ProbLoss*. The probability difference of winning and losing games is captured by *ProbDiff*. We define 4 dummy variables which indicate whether a team is strongly expected to win *(SEW)*, weakly expected to win (*WEW)*, weakly expected to lose *(WEL) or* strongly expected to lose *(SEL)*. Depending on which underlying probability measure is used, we label the above variables by [a] (when *ProbWin* is used) and by [b] (when *ProbDiff*. is used). *PostMarch* is equal to one if a game is played in April, May, or June, and zero otherwise; *AIM is* equal to one if the club is listed on the AIM and zero otherwise; *Home* is equal to one if the game is a home game and zero in case of an away game; *Cup* is equal to one if the game is a national cup game and zero otherwise. Ordered probit is used when the dependent variable is *GoalDiff*, and probit regressions are used with *Win* and *Loss* as dependent variables. The p-values of the estimated coefficients are in parentheses. All regressions have 916 observations.

Quality of odds [a]	Model 1		Model 2		Model 3	
	Ordered probit		Probit		Probit	
Dep. Variable:	GoalDiff		Win		Loss	
Panel A:						
Constant			-8.03	-6.90	8.43	6.99
			(0.000)	(0.000)	(0.000)	(0.000)
ProbWin	0.04		0.04		-0.04	
	(0.000)		(0.000)		(0.000)	
SEW[a]		0.58		0.66		-0.82
		(0.000)		(0.000)		(0.000)
WEL[a]		-0.13		-0.05		0.09
		(0.226)		(0.727)		(0.507)
SEL[a]		-0.75		-0.52		0.78
		(0.000)		(0.001)		(0.000)
PostMarch	-0.09	-0.08	-0.08	-0.08	0.06	0.06
	(0.303)	(0.335)	(0.457)	(0.488)	(0.627)	(0.643)
AIM	1.82	1.85	6.37	6.47	-7.07	-7.17
	(0.077)	(0.073)	(0.000)	(0.000)	(0.000)	(0.000)
Home	-0.12	0.04	-0.11	0.04	0.14	0.02
	(0.189)	(0.669)	(0.334)	(0.726)	(0.227)	(0.892)
Cup	-0.15	-0.02	-0.06	0.06	0.34	0.25
	(0.216)	(0.861)	(0.728)	(0.712)	(0.062)	(0.146)
Year9900	0.08	0.07	0.11	0.11	-0.16	-0.15
	(0.368)	(0.390)	(0.319)	(0.333)	(0.187)	(0.207)
Year0001	0.04	0.05	0.13	0.13	-0.04	-0.04
	(0.641)	(0.593)	(0.263)	(0.249)	(0.754)	(0.753)
Team Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.068	0.059	0.126	0.111	0.158	0.146

Table VI continues on the next page.

Table VI – Continued

Quality of odds [b]	Model 4		Model 5		Model 6	
	Ordered probit		Probit		Probit	
Dep. Variable:	GoalDiff		Win		Loss	
Panel B:						
Constant			-6.73	-6.82	6.83	6.92
			(0.000)	(0.000)	(0.000)	(0.000)
ProbDiff	0.02		0.02		-0.02	
			(0.000)		(0.000)	
SEW[b]		0.53		0.60		-0.71
		(0.000)		(0.000)		(0.000)
WEL[b]		-0.32		-0.26		0.32
		(0.001)		(0.035)		(0.011)
SEL[b]		-1.01		-0.90		1.17
		(0.000)		(0.000)		(0.000)
PostMarch	-0.08	-0.07	-0.08	-0.06	0.05	0.03
	(0.338)	(0.447)	(0.486)	(0.590)	(0.663)	(0.795)
AIM	1.81	1.92	6.36	6.53	-7.05	-7.23
	(0.079)	(0.063)	(0.000)	(0.000)	(0.000)	(0.000)
Home	-0.11	0.02	-0.10	0.01	0.13	0.01
	(0.229)	(0.791)	(0.389)	(0.903)	(0.270)	(0.916)
Cup	-0.13	-0.03	-0.03	0.06	0.32	0.24
	(0.300)	(0.831)	(0.834)	(0.728)	(0.071)	(0.161)
Year9900	0.08	0.10	0.11	0.13	-0.16	-0.19
	(0.352)	(0.261)	(0.307)	(0.250)	(0.168)	(0.112)
Year0001	0.04	0.07	0.13	0.15	-0.04	-0.07
	(0.624)	(0.403)	(0.251)	(0.175)	(0.722)	(0.538)
Team Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.067	0.061	0.125	0.115	0.157	0.148

Table VII
Market reactions to odds

This table presents the average (cumulative) abnormal returns ((C)ARs) in basis points after the betting odds are posted. We define 4 dummy variables which indicate whether a team is strongly expected to win *(SEW),* weakly expected to win (*WEW),* weakly expected to lose *(WEL) or* strongly expected to lose *(SEL).* Depending on which underlying probability measure is used, we label the above variables by [a] (when *ProbWin* is used*)* and by [b] (when *Probdiff.* is used). The p-values (in parentheses) of the t-test and the Wilcoxon signed-rank test are presented in the first and second rows following the average abnormal returns respectively.

	N	Reaction to odds [a]			N	Reaction to odds [b]		
		AR(-2)	AR(-1)	CAR(-2,-1)		AR(-2)	AR(-1)	CAR(-2,-1)
SEW	357	5.96	-6.42	-0.47	271	11.38	-6.28	5.09
p-value of t-test		(0.568)	(0.530)	(0.974)		(0.380)	(0.601)	(0.775)
p-value Wilcoxon		(0.635)	(0.666)	(0.849)		(0.973)	(0.903)	(0.877)
WEW	227	-15.91	8.10	-7.82	289	-15.51	2.18	-13.33
p-value of t-test		(0.218)	(0.522)	(0.650)		(0.157)	(0.849)	(0.368)
p-value Wilcoxon		(0.222)	(0.221)	(0.679)		(0.123)	(0.277)	(0.587)
WEL	186	10.71	-12.02	-1.31	241	8.65	-11.40	-2.75
p-value of t-test		(0.459)	(0.345)	(0.951)		(0.463)	(0.275)	(0.871)
p-value Wilcoxon		(0.166)	(0.077)	(0.740)		(0.131)	(0.106)	(0.597)
SEL	146	-18.85	14.84	-4.01	115	-25.50	28.66	3.16
p-value of t-test		(0.287)	(0.478)	(0.888)		(0.227)	(0.265)	(0.929)
p-value Wilcoxon		(0.517)	(0.609)	(0.468)		(0.832)	(0.258)	(0.426)

Table VIII
Market reactions to odds: regression results

This table presents the OLS regression results explaining the cumulative abnormal returns (CARs) after the betting odds are posted. The dependent variables are CAR(-2,-1). We define 4 dummy variables which indicate whether a team is strongly expected to win *(SEW),* weakly expected to win (*WEW),* weakly expected to lose *(WEL) or* strongly expected to lose *(SEL).* Depending on which underlying probability measure is used to define the above categorization, we label the above variables by [a] (when *ProbWin* is used*)* and by [b] (when *ProbDiff.* is used). *PostMarch* is equal to one if a game is played in April, May, or June, and zero otherwise; *AIM* is equal to one if the club is listed on the AIM and zero otherwise; *Home* is equal to one if the game is a home game and zero in case of an away game; *Cup* is equal to one if the game is a national cup game and zero otherwise. The p-values of the estimated coefficients are in parentheses. All regressions have 916 observations.

	Specification [a] CAR(-2,-1)	Specification [b] CAR(-2,-1)
Constant	-14.26	-26.21
	(0.960)	(0.927)
SEW	19.42	33.16
	(0.481)	(0.230)
WEL	6.14	6.47
	(0.835)	(0.810)
SEL	-1.99	6.96
	(0.951)	(0.840)
PostMarch	14.04	14.50
	(0.561)	(0.549)
AIM	18.54	28.11
	(0.949)	(0.922)
Home	6.39	4.08
	(0.792)	(0.868)
Cup	-63.78	-66.50
	(0.063)	(0.053)
Year9900	-11.55	-11.02
	(0.629)	(0.643)
Year0001	-29.43	-29.43
	(0.220)	(0.218)
Team Dummies	Yes	Yes
R^2	0.036	0.034
F-Statistics	0.99	1.02
Prob > F	0.482	0.432

Table IX
Predictability of betting odds

This table presents the average (cumulative) abnormal returns ((C)ARs) in basis points subsequent to the soccer games, categorized on the basis of the betting odds. We define 4 dummy variables which indicate whether a team is strongly expected to win *(SEW),* weakly expected to win (*WEW),* weakly expected to lose *(WEL) or* strongly expected to lose *(SEL).* Depending on which underlying probability measure is used, we label the above variables by [a] (when *ProbWin* is used*)* and by [b] (when *Probdiff.* is used). The p-values (in parentheses) of the t-test and the Wilcoxon signed-rank test are presented in the first and second rows following the average abnormal returns, respectively.

	Specification [a]				Specification [b]			
	N	AR(1)	AR(2)	CAR(1,2)	N	AR(1)	AR(2)	CAR(1,2)
SEW	357	28.86	14.95	43.81	271	30.69	19.33	50.02
p-value of t-test		(0.034)	(0.138)	(0.010)		(0.071)	(0.118)	(0.020)
p-value Wilcoxon		(0.024)	(0.050)	(0.010)		(0.085)	(0.065)	(0.031)
WEW	227	-0.04	-29.73	-29.76	289	6.80	-22.65	-15.86
p-value of t-test		(0.998)	(0.065)	(0.188)		(0.565)	(0.082)	(0.380)
p-value Wilcoxon		(0.308)	(0.467)	(0.724)		(0.082)	(0.895)	(0.682)
WEL	186	-2.51	-23.23	-25.74	241	-2.08	-22.05	-24.12
p-value of t-test		(0.903)	(0.162)	(0.381)		(0.903)	(0.114)	(0.326)
p-value Wilcoxon		(0.412)	(0.728)	(0.697)		(0.129)	(0.354)	(0.779)
SEL	146	12.68	-13.24	-0.56	115	16.54	-9.08	7.46
p-value of t-test		(0.507)	(0.393)	(0.982)		(0.455)	(0.613)	(0.798)
p-value Wilcoxon		(0.451)	(0.319)	(0.918)		(0.256)	(0.696)	(0.865)

Table X
Predictability of betting odds: regression results

This table presents the OLS regression results explaining the cumulative abnormal returns (CARs) subsequent to the soccer games. The dependent variables are CAR(1,2). We define 4 dummy variables which indicate whether a team is strongly expected to win *(SEW),* weakly expected to win (*WEW),* weakly expected to lose *(WEL) or* strongly expected to lose *(SEL).* Depending on which underlying probability measure is used, we label the above variables by [a] (when *ProbWin* is used*)* and by [b] (when *ProbDiff.* is used). *PostMarch* is equal to one if a game is played in April, May, or June, and zero otherwise; *AIM is* equal to one if the club is listed on the AIM and zero otherwise; *Home* is equal to one if the game is a home game and zero in case of an away game; *Cup* is equal to one if the game is a national cup game and zero otherwise. The p-values of the estimated coefficients are in parentheses. All regressions have 916 observations.

	Specification [a] CAR(1,2)	Specification [b] CAR(1,2)
Constant	-130.58	-127.83
	(0.704)	(0.710)
SEW	81.19	70.65
	(0.014)	(0.033)
WEL	1.49	-7.66
	(0.966)	(0.812)
SEL	36.04	28.10
	(0.353)	(0.495)
PostMarch	-32.94	-32.38
	(0.254)	(0.263)
AIM	43.60	49.05
	(0.899)	(0.887)
Home	-9.71	-5.02
	(0.737)	(0.864)
Cup	-3.68	-3.73
	(0.928)	(0.928)
Year9900	59.10	62.20
	(0.039)	(0.029)
Year0001	57.92	59.07
	(0.043)	(0.039)
Team Dummies	Yes	Yes
R^2	0.036	0.034
F-Statistics	1.38	1.32
Prob > F	0.10	0.14