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Information Salience, Investor Sentiment, and Stock Returns: the Case of British Soccer Betting [¶]

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Abstract

Soccer clubs listed on the London Stock Exchange provide a unique way of testing stock price reactions to different types of news. For each firm, two pieces of information are released on a weekly basis: experts' expectations about game outcomes through the betting odds, and the game outcomes themselves. The stock market reacts strongly to news about game results, generating significant abnormal returns and trading volumes. We find evidence that the abnormal returns for the winning teams do not reflect rational expectations but are high due to overreactions induced by investor sentiment. This is not the case for losing teams. There is no market reaction to the release of new betting information although these betting odds are excellent predictors of the game outcomes. The discrepancy between the strong market reaction to game results and the lack of reaction to betting odds may not only be the result from overreaction to game results but also from the lack of informational content or information salience of the betting information. Therefore, we also examine whether betting information can be used to predict short-run stock returns subsequent to the games. We reach mixed results: we conclude that investors ignore some non-salient public information such as betting odds, and betting information predicts a stock price overreaction to game results which is influenced by investors' mood (especially when the teams are strongly expected to win).

JEL codes: G12, G14

Keywords: information salience, investor sentiment, investor attention, sports betting, soccer, football, economics of sports, market efficiency

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Abstract

Soccer clubs listed on the London Stock Exchange provide a unique way of testing stock price reactions to different types of news. For each firm, two pieces of information are released on a weekly basis: experts' expectations about game outcomes through the betting odds, and the game outcomes themselves. The stock market reacts strongly to news about game results, generating significant abnormal returns and trading volumes. We find evidence that the abnormal returns for the winning teams do not reflect rational expectations but are high due to overreactions induced by investor sentiment. This is not the case for losing teams. There is no market reaction to the release of new betting information although these betting odds are excellent predictors of the game outcomes. The discrepancy between the strong market reaction to game results and the lack of reaction to betting odds may not only be the result from overreaction to game results but also from the lack of informational content or information salience of the betting information. Therefore, we also examine whether betting information can be used to predict short-run stock returns subsequent to the games. We reach mixed results: we conclude that investors ignore some non-salient public information such as betting odds, and betting information predicts a stock price overreaction to game results which is influenced by investors' mood (especially when the teams are strongly expected to win).

1. Introduction

It is now widely acknowledged that individuals have limited information processing abilities. As Herbert Simon (1978: 13) mentions "*many of the central issues of our time are questions of how we use limited information and limited computational ability to deal with enormous problems whose shape we barely grasp*". As a consequence of this limited processing ability, investors may concentrate their time and attention to highly visible, easy to process information. In other words, limited processing ability may generate limited attention. One of the consequences is that reactions to public news depend on its relative salience: the higher the information salience (i.e. media coverage), the faster the public information is processed by investors and is reflected in the share prices. In the recent past, several articles have reported empirical evidence about asset price reactions to public news consistent with the salience theory. Studying closed-end country funds, Klibanoff et al. (1998) show that country-specific information which does not receive large media coverage is incorporated only gradually into the share prices. In a case study, Huberman and Regev (2001) describe EntreMed's substantial and permanent stock price rise after a 'special report' on new cancer-curing drugs on the front page of the Sunday edition of the *New York Times* (NYT). This is remarkable as the NYT article did not contain any new information: the potential breakthrough had already been reported five months earlier in the scientific press (an article in Nature) and in the popular press (including the NYT itself but then not on a prominent place – in a tiny article on page A-28). Chan (2003) studies market returns following prominent public news, i.e., firm-related information that made the headlines or a lead article, and finds that investors react slowly to bad news. A recent study by Gilbert et al. (2007) shows that investor inattention influences the aggregate stock market.

Investors' constraints in information processing are not only characterized by ignoring relevant news but also by misinterpreting the relevance of news. In particular, studies on behavioral finance argue that investors are subject to sentiment (e.g. Delong et al., 1990).[1] Some recent papers study the impact of exogenous changes in investor emotions on share prices (e.g. Kamstra et al, 2003). When arbitrage against sentiment-prone investors is risky and costly, mispricing may persist in financial markets (Shleifer and Vishny, 1997). An example of investor sentiment is the study by Edmans, Garcia, and Norli (2007) who investigate the impact of international soccer results on stock market indices. They find a significant market decline after losses by national soccer teams in international soccer competitions. The authors demonstrate that this loss effect is caused by a change in investor mood.[2] Indeed, soccer results influence investor sentiment but have little direct economic impact. Edmans et al. also show that the stock market effect is stronger for countries with a prominent soccer tradition, for games in the World Cup and for elimination games, and for smaller stocks.

English and Scottish professional soccer teams listed on the London Stock Exchange (LSE) provide a unique way of studying the stock price reaction to different pieces of news while controlling for the informational content. For each of these stocks, betting markets and stock markets co-exist and two pieces of information are released on a weekly basis from August to June: betting odds and game results. Listed soccer teams are also interesting study objects because the performance of the team is greeted with lots of emotion and media coverage. The objective of this paper is not to identify a profitable trading strategy, but to analyse the impact of investor sentiment and information salience on news absorption by the stock market by studying the *difference* in the market reactions to these two types of news.

Soccer betting in the UK occurs via a fixed-odds procedure: the odds are posted several days prior to the game and are very rarely altered in response to betting before the event. This fixed-odds betting system is different from the pari-mutuel system (as often used in betting on horse races) and from the point spread betting system (used for the most popular sports in the US), in which odds

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[1] Investor sentiment can be broadly defined as "a belief about future cash flows or investment risks that is not justified by the facts at hand" (Baker and Wurgler, 2007:129). While one approach to study investor sentiment uses psychological biases of individual investors to explain investor underreaction or overreaction to news (Barberis et al., 1998, and Daniel at al., 1998), another approach develops aggregate measures of sentiment in stock markets (Baker and Wurgler, 2006).

[2] The previous literature in psychology shows that (inter)national sports events can significantly affect people's sentiment about their own personal lives and the mood of an entire country (e.g. White, 1989).

respond to betting volumes and thus represent a consensus in investors' opinions. Within a fixed-odds betting system, the odds represent only the bookmakers' (or their experts') opinions.[3] Hence, investors are informed on a weekly basis about the experts' beliefs about the game outcomes (through the odds that the bookmakers publish), and the game results. Both these types of news provide new information about the performance of the teams/firms. However, they differ in four crucial ways. First, betting odds represent experts' opinions about game outcomes while game results represent information about realizations. Second, betting odds offer short-lived information. After two trading days, the game outcome is known and the information value contained by the betting odds has evaporated. As a consequence, if betting odds do contain valuable information, markets must be fast in processing this information. Third, while a victory or a defeat of soccer clubs clearly shifts investor mood, betting odds hardly have any impact on sentiment. Finally, 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.

Our paper is structured around four questions: (i) Do victories (and losses) trigger significant stock price and trading volume increases (decreases)?, (ii) Do the market reactions reflect rational expectations or overreaction induced by information salience/investor sentiment?, (iii) Does the release of betting information trigger stock price and trading volume reactions?, and (iv) Can betting odds predict stock returns and do investor sentiment or information salience explain the differences in the market reactions to the two correlated sets of news?

Our findings yield a mix of results. Our first question is answered affirmatively: the market reacts strongly to game results, generating abnormal trading volumes and abnormal returns in the days following the games. Over a three-day period subsequent to the game, we observe an average abnormal return of 88 basis points subsequent to a win, of -101 basis points subsequent to a defeat, and of -33 basis points following a draw. We also find that the market processes good news faster than bad news, a result consistent with the literature (see e.g. Hong, Lim and Stein, 2000; Chan, 2003). After a victory, a significant positive average abnormal return is observed on the first trading day subsequent to the games, but not on the following days. Bad news (i.e., defeats) is processed more slowly as we observe significant negative abnormal returns on the first three trading days after a game. These results suggest that information about game results is used extensively by investors. Since the game results represent 'hard' information about future earnings, our study is related to those on stock price (under-)reaction to earning announcements (see e.g. Ball and Brown, 1968; Bernard and Thomas, 1990; Chan, Jegadeesh, and Lakonishok, 1996; Frazzini, 2006). Our paper is

[3] 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.

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 sports clubs.[4]

Our second question asks whether the above market reactions reflect rational expectations or overreaction induced by investor sentiment or information salience. The results yield nuanced answers. The rational expectations hypothesis argues that there is a clear and direct relation between the financial performance as measured by the stock returns, and the team's performance 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 in the lucrative European competition (the UEFA Champions' League) in the following season.[5] 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.[6] Third, field performance has a direct impact on ticket sales, merchandising and sponsorship revenues. Soccer games also reveal information about the players' quality to investors. For all these reasons, game-outcome related information should have an impact on the stock price.[7] Consistent with the rational expectations hypothesis, we find that the average abnormal returns of about 1% (-1%) over the first three days following a win (a loss) is comparable to the average sales revenue derived from a given game for a soccer club. The market reactions to game outcomes are also not transitory in the short run. Firms without a large institutional owner are not subject to stronger market reactions. However, a set of other tests gives more support to the investor sentiment explanation. For instance, smaller clubs are associated with stronger market reactions to game results. Furthermore, investors react strongly to a win, especially when the win was strongly expected (and hence should not create a surprise effect). Investor sentiment thus causes an asymmetric share price reaction: wins trigger abnormal returns due to a positive sentiment but,

[4] The former study investigates whether share prices of soccer clubs listed on the London Stock Exchange are influenced by the soccer teams' weekly sporting performances. They find a positive average abnormal return following victories on the first post-game day, and negative average abnormal returns following defeats and draws. Renneboog and Van Brabant (2000) also document that investors respond asymmetrically to wins and losses, and that playoff games have a larger impact on returns than regular-season games. Brown and Hartzell (2001) study the impact of NBA game results on the equity prices of Boston Celtics Limited Partnership and confirm that the results of the Celtics' basketball games significantly affect partnership share returns, trading volume, and volatility.

[5] For example, for the season 2000-2001, Manchester United receives national television revenues of Euro 29.3 million and Champions' League participation revenue of Euro 22.2 million. Falconieri et al. (2004) provide more data on television revenues in European soccer.

[6] 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.

[7] Professional investors have become important investors in soccer clubs in Europe. The Dow Jones Stoxx Football Index was introduced in 2002 to track the stock prices of soccer clubs listed on European stock exchanges.

consistent with the rational expectations hypothesis, the market reaction to a loss is weaker the higher its ex ante probability.

Our third question is answered negatively: we cannot find any evidence of a market reaction (neither in volume nor in returns) following the release of betting odds. It may be that the odds do not contain any new information unknown to investors even though we demonstrate that bookmakers' experts are excellent predictors of the games' results. Alternatively, the odds can contain new information which is not processed by investors or is too costly to trade on. The absence of a market reaction may hence be explained by a lack of information salience, or by high bid/ask spreads. Our study differs from previous analyses of the reaction to public news events in two important ways. First, we analyse the *difference* in the reaction to two pieces of news, i.e. betting odds versus game results that differ in their sentiment and salience levels. Second, one type of news (the betting odds) in our study is released with high frequency and is short-lived. After two trading days, our betting odds do not contain further information as the game outcomes are known. Since betting odds represent opinions about earnings-related information, our study is also related to the literature on (under-)reaction to *revisions* of earnings forecasts (see e.g. Givoly and Lakonishok, 1979; Chan et al., 1996; Womack, 1996; Daniel et al., 1998). Combining analysts' forecasts and salience (media coverage) levels, Bonner et al. (2005) show that the investors' reactions to revisions of analysts' forecasts depend on the media coverage of these revisions.[8] However, there are also crucial differences between information released by bookmakers and that released by equity-analysts. Bookmakers, whose expected profits are determined by betting odds, are less subject to the biases documented about these analysts, i.e., systematic optimism (Easterbrook and Nutt, 1999), conflicts of interests for analysts working for brokerage firms (Michaely and Womack, 1999), and incentives to herd (see, e.g., Trueman, 1994; Welch, 2000; Hong, Kubik and Solomon, 2000; Clement and Tse, 2004).

Our fourth question is whether betting odds can be used to predict the stock returns subsequent to the game outcome, and whether information salience or investor sentiment explains the differential market reactions to betting odds and game results. To test the predictive power of fixed odds on stock returns, we compute the average cumulative abnormal returns (*ACARs*) conditional on the strength of the experts' predictions as reflected in the betting odds (strongly

[8] In the finance literature, the consequences of imperfect information processing ability have been studied in various environments. Barber and Odean (2008) show that individual investors are net buyers of "attention-grabbing" stocks. Likewise, Hirshleifer and Teoh (2003) study the consequence of investors' limited attention to the way firms release financial information (e.g., *pro forma* earning measures versus GAAP earnings measures). Hirshleifer et al. (2007) find that the immediate market reaction to earnings surprises is weaker when investors are distracted by a greater number of earnings announcements on the same day. In addition, Dellavigna and Pollet (2008) show that earnings announcements on Fridays, when investor inattention is more likely, generate less immediate market responses than those on other weekdays. Foucault et al. (2003) use a costly-information-processing explanation to provide a rationale for the fact that SOES day-traders make profits against NASDAQ dealers. Regarding mutual fund inflows, Barber et al. (2005) show that mutual fund investors are more sensitive to salient fees (such as front-end loads) than to operational expenses.

expected to win, weakly expected to win, strongly expected to lose). In particular, we observe that the 3-day (statistically significant) average abnormal return is 64 basis points subsequent to the game outcome when the team was strongly expected to win. This suggests that betting odds contain new information to investors (which is in contrast to the rational expectations hypothesis). A naïve 60-day trading strategy whereby an investor buys a share in a firm that is strongly expected to win and sells after 3 months (regardless of the intermediate news) yields on average between 175 and 245 basis points over and above the expected returns. Remarkable is that significant abnormal returns only emerge when teams are strongly expected to win and not when teams are weakly expected to win or strongly expected to lose. The asymmetric predictability of betting odds to stock returns following wins and losses and the fact that there is still a market reaction when the outcome is most anticipated, does not support the information salience hypothesis. These results imply that investor sentiment influences news absorption by the stock market, and betting information predicts an overreaction in stock prices.

The structure of this paper is as follows. Section 2 provides a description of the fixed-odd betting system. Section 3 discusses the dataset and Section 4 focuses on methodology. Section 5 presents the results while Section 6 discusses their robustness. Finally, Section 7 concludes.

2. The Fixed-Odds Betting System

The most prominent form of soccer betting in the UK is the fixed-odds system. In this system, the experts of the bookmakers (i.e. companies that provide betting services) generate betting odds for the possible game outcomes (a win, draw, or loss) in the English and Scottish leagues a few days before a game. Betting odds reflect the amount of money that bookmakers will pay out to bettors on winning bets per unit of a bet. Once the odds are posted, they are fixed over time and it is extremely rare that they change prior to the kick-off of the game. In this respect, the fixed-odds system is different from other betting systems such as pari-mutuel (as often used in betting on horse races) or the point-spread betting (on basketball, ice hockey, or football in the US), which reflect and react to the amount of money bet on each possible outcome up to the start of the event.[9]

Consider the following example. The odds on a soccer game between Chelsea (the home team – on whose field the game is played) versus Bolton (the away team) are 5/7 for a home win, 14/5 for an away win, and 13/5 for a draw. These odds quote the net total amount of money that will be paid out to the bettor, should he make a correct bet, relative to his stake. Odds of 5/7 ("five-

[9] Avery and Chevalier (1999) study how investor sentiment changes over time through the analysis of the price path of betting odds on the point spread of game outcomes in US football betting. Such an analysis is not possible for UK soccer betting as here the odds are fixed and hence do not change prior to the game.

to-seven") for a home win imply that the bettor can make a £5 net profit on a £7 stake of initial investment if Chelsea wins the game. Should he win, the bettor always gets his original stake back, so the bettor would receive a total of £12 (= £5 +£7) on a £7 stake in case of a home win. Similarly, odds of 14/5 for an away win means that the bettor will make £14 net profit on a £5 stake in the less likely event of a win by Bolton. Odds of 13/5 for a draw implies that the bettor will make £13 net profit on a £5 stake if there is no winner in the game between Chelsea and Bolton.

The revenues of the bookmakers for their services in the fixed odds-system are also different from those in the pari-mutuel system. In the latter system, a bookmaker's revenue is a percentage of the total amount bet. In the fixed-odds system, the bookmaker's revenue is measured by the so-called 'over-roundness' of the book, which represents his potential profit margin. In the above example, the amount of the bet required to receive £ 100 for each outcome is calculated as follows:

Home win: 100/(1+5/7) = £ 58.3

Away win: 100/(1+14/5) = £ 26.3

Draw: 100/(1+13/5) = £ 27.8

The over-roundness of the book is the amount by which the actual book exceeds 100: over-round = 58.3+26.3+27.8-100 = £12.4. Thus, if the book is balanced (i.e. the amounts bet on each outcome are inversely related to the odds), the bookmaker takes a proportional stake of 58.3, 26.3 and 27.8 in the three game outcomes, and he receives a total amount of 58.3+26.3+27.8= £112.4. Whatever the outcome of the game, the bookmaker will pay out £100 only and keep the remaining £12.4. His potential return is then 12.4/112.4=11.05% of the total amount bet if the book is balanced.

It is important to note that, although bookmakers aim at a 'balanced book' which yields them the above a return, they also face considerable risks. In the more usual case of an imbalanced book, the bookmaker may incur a lower (even negative) or higher return than the over-roundness.

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 one plus 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 (including the one unit of money bet) 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 the bookmaker's beliefs. These measures are equivalent to the implied probabilities in the asset pricing literature.

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

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

The denominator in (1) and (2) is one plus the over-roundness. For the betting odds in our sample, over-roundness has a mean of 0.122 and a standard deviation of 0.005, which signifies that bookmakers have a potential return of 10.9% (0.122 / 1.122 = 0.109) of the invested (bet) amounts. We will discuss further how betting odds represent the expectations of game outcomes in Section 4.1.

3. Data Description

Twenty UK soccer clubs are listed on the LSE: 12 clubs on the official market and 8 clubs on the Alternative Investment Market (AIM)[10]. In addition, the shares of 4 clubs are traded on OFEX[11], 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.[12] 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 average market capitalization for the period 1999-2002. The most valuable club is 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 soccer games, including league games and national cup games[13], played by the clubs of Table I during the three seasons in the period 1999-2002 were purchased from Mables-

[10] 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 Forest, both in December 2001. Therefore, we do not include these clubs into our sample.
[11] 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.
[12] Celtic is the only Scottish soccer club in our sample. Excluding this firm does not affect our results.
[13] When we drop national cup games (e.g. the FA cup games in England) from our sample, our results remain unchanged.

Tables, an internet soccer information provider. Our sample does not comprise all the games because those played by non-listed teams cannot be 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 Ladbrokes, the betting and gaming division of the Hilton Group.[14] 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 that 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. 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.

4. Methodology

4.1. From Betting Odds to Expectations about Game Outcomes.

We use a number of measures, including both continuous variables and dummy variables, to capture the bookmakers' expectations about game outcomes. In addition to using the probabilities to win and to lose (*ProbWin* and *ProbLoss*) which reflect the experts' beliefs on the outcome of the games (see Section 2), we also use a second measure to capture the experts' expectations about game uncertainty and their impact on stock returns: the probability difference (*ProbDiff*) of winning and losing games. Thus, game uncertainty is reflected by:

$$ProbDiff_i = ProbWin_i - ProbLoss_i \qquad (3)$$

Note that we indirectly include in this measure the 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 the *ProbDiff*, the more a win is expected relative to a loss. When *ProbDiff* decreases and approaches 0, the outcome becomes more uncertain. When *ProbDiff* is negative, a loss is more likely to occur than a win. Therefore, for

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

games with the most uncertain outcomes, both *ProbWin* and *ProbLoss* should equal 33.3% and *ProbDiff* equals 0.

In order to group the games by type of expectations, four dummy variables are constructed by utilizing the above continuous variables on bookmakers' 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. We find that 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* ∈ [0.35, 0.45], and zero otherwise. We find that 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* ∈ [0, 0.3], and zero otherwise.

• *WEL* (*weakly expected to lose*): *WEL[a]* is equal to one if *ProbWin* ∈ [0.25, 0.35], and zero otherwise. We find that 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* ∈ [-0.3, 0], and zero otherwise.

• *SEL* (*strongly expected to lose*): *SEL[a]* is equal to one if *ProbWin* < 0.25, and zero otherwise. We find that 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 (see below in Section 6 for the robustness checks).

4.2. Abnormal Return Computation

Denoting $P_{i,t}$ the closing price of stock *i* on day *t*, and $Div_{i,(t-1,t)}$ 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)[15]. We opt for this index to control for the size effect on stock returns.[16]

[15] 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). An abnormal return is that part of the total return that cannot be explained by the covariance between stock returns and market returns.

As some soccer clubs may suffer from non-synchronous trading, we add three leads and three lags of market returns to the market model (See Dimson, 1979). Thus, the market model we consider is estimated over 1008 daily observations for each of the 16 clubs:

$$r_{i,t} = \alpha_i + \sum_{\tau=-3}^{+3} \beta_{i\tau} r_{m,t+\tau} + \varepsilon_{i,t} \qquad i = 1, \ldots, 16, \; t = 1, \ldots, 1035 \qquad (5)$$

where $r_{m\tau}$ is the return of FTSE All Small index on day τ. Denoting the 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[17]:

$$AR_{it} = r_{it} - a_i - r_{m,t} \sum_{\tau=-3}^{+3} b_{i\tau} \qquad i = 1, \ldots, 16, \; t = 1, \ldots, 1035 \qquad (6)$$

The standard errors of the abnormal returns are estimated using the cross section of abnormal returns in the event period. This approach allows for event-induced increases in variance (MacLinlay, 1997: 27-28). To increase the efficiency and power of the cross-sectional test and allow for return heteroskedasticity, Boehmer, Musumeci, and Poulsen (1991) make an adjustment to the above test and propose a 'standardized cross-sectional' test which incorporates information on stock returns variance from both the estimation and the event windows. Even though firms in our sample come from the same industry (i.e. soccer) and hence are less subject to return heteroskedasticity, we also apply this methodology as a robustness check. First, the abnormal returns of a firm are standardized by the estimation-period standard deviation (estimated over the full sample period in our case). Second, the test statistic is then obtained by dividing the average standardized abnormal return (in the event periods) by its cross-sectional standard errors. In other words, this approach gives relatively smaller weights to returns of firms with larger variance, and the test is consequently robust even if the returns are drawn from different distributions. The results following from the Boehmer et al. method are similar to the ones obtained from the method described above.

Given that there may be multiple games played on the same weekend and that there are some periods during the year without weekend games (summer and winter stops), we account for event clustering in two ways. First, we test the significance of the ARs using 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 Wednesday (subsequent to the game). We take the weekend as the

[16] The results in this paper do no depend upon the choice of the market index. Using the FT All Share index yields similar results.
[17] We also corrected the systematic risk for regression to the mean, but this does not influence the results. Alternatively, we adopted a regression approach to measure abnormal returns by adding dummy variables for the event days to the market model. Our results do not change.

event date and refer to Thursday, Friday, Monday, Tuesday and Wednesday as day -2, -1, 1, 2 and 3, respectively. For instance, 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, 3. The cumulative abnormal return between days z and z', ($z, z' \in \{-2,\ldots, 3\}, z' > z$) is defined as $CAR(z,z') = AR(z) + \ldots + AR(z')$. The average abnormal returns and the average cumulative abnormal returns are denoted by *AAR(z)* and *ACAR(z,z')*.

5. Results

Our approach to study the news absorption by the stock market is structured as follows. First, we examine the price and volume reactions to game outcomes. Second, we investigate whether these results can be explained by rational expectations, or investor sentiment. Third, we examine the predictive power of betting odds with regard to game outcomes and the market reaction to the release of betting information. Finally, we study the predicative power of betting odds to post-game stock returns and examine whether the results can be explained by investor sentiment or information salience.

5.1. Stock Price and Trading Volume Reactions to Game Results

Panel A of Table III exhibits the average cumulative abnormal returns over the three days following the soccer matches that 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 average abnormal return of 53 basis points on day 1 (statistically significant at the 1% level), and a positive average abnormal return of 88 basis points over the first three days (statistically significant at the 1% level). A loss is followed by a significantly negative average return of 28 basis points on the first day following a game (significant at the 5% level) and a negative average return of 101 basis points over the first three days following a game (significant at the 1% level). The mean abnormal return subsequent to a draw is negative but not statistically different from zero.

An interesting related finding is that the market seems to be faster at processing good news than bad news. This finding is in line with Hong, Lim and Stein (2000) and Chan (2003) who also conclude that investors react more slowly to bad news. We show that after a win, about 60% of the three-day abnormal return is generated on the first day. Conversely, after a loss, only 28% of the three-day abnormal return is generated on the first day. However, measured over a three-day window, the market reactions to a victory and a defeat are similar in magnitude (88 versus 101 basis points, respectively). This is different from the results obtained in Brown and Hartzell (2001) who find that for US professional basketball games, the market reaction to a defeat is much stronger than to a victory.

[Insert Table III about here]

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 the 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 of 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 reactions 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[18] games played by teams belonging to the top six in the English First or Second League. *Relegation* games are non-cup games played by teams ranked at the fifteenth position or lower in every league. *Top* games are non-cup games played by teams belonging to the top six in the English Premier League or top two in the Scottish Premier League as they compete for participation in the European championships. Finally, *Other* represents the other non-cup games which were not included in the above categories, but were also played in April, May or June. The results show strong statistically significant average abnormal returns for the promotion candidates.[19] For example, a victory triggers a three-day average abnormal return of 4.11% (statistically significant within the 5% level) while a defeat leads to a negative price correction of 3.05% (statistically significant within the 5% level). The abnormal returns for the relegation candidates and the top teams competing for the participation right to European soccer, i.e. the UEFA Champions League, are large but lack statistical significance (possibly due to small sample sizes).

[18] The cup competitions are different from regular league competitions: all the clubs of the Premier League and Divisions 1, 2 and 3 can participate in the cup competitions which is a knock-out competition with immediate elimination upon defeat.
[19] Tables are available upon request.

We also test the market reaction to game results by estimating 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 scored by the opposing team 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:

$$CAR(1,j) = \alpha_0 + \alpha_1.Win + \alpha_2.Loss + \beta.ControlVariables + \varepsilon \qquad (j=1,2,3) \qquad (7)$$

$$CAR(1,j) = \alpha_0 + \alpha_1.GoalDiff + \beta.ControlVariables + \varepsilon \qquad (j=1,2,3) \qquad (8)$$

where *ControlVariables* include the following dummy variables: *PostMarch* equals one if a game is played in April, May, or June, and zero otherwise; *AIM* equals one if the club is listed on the AIM and zero in case of a listing on the Official Market of the LSE; *Home* equals one if the game is a home game and zero in case of an away game; *Cup* 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 IV confirm that there is a strong positive reaction to a victory. In all regressions, *GoalDiff* and *Win* are significantly positive at the 1% level.[20] In addition, the *PostMarch* dummy is not significant in all regressions, which implies that the significance of our findings is not caused by the effect of a limited number of important games played late in the season.

As a robustness check, we also use White's (1980) standard errors[21] in the regressions and we cluster the standard errors by firm, to account for heteroskedasticity and potential dependence in residuals. This does not change our results. We use the ARMA(1,1) model to take into account autocorrelation when estimating abnormal returns, and use a bootstrapping method to allow for non-normal distribution of residuals of regressions in the paper. Our results remain unchanged (see Section 6.3 for details of these robustness checks).

[Insert Table IV about here]

To test investors' reactions to game results in terms of trading volume, we proceed as follows. First, we define a measure of abnormal volume (AV) around the event dates[22]:

$$\mathrm{AV}(1,2) = \frac{\mathrm{Volume}\,(t=1) + \mathrm{Volume}\,(t=2)}{\mathrm{Volume}\,(t=-1) + \mathrm{Volume}\,(t=-2)} - 1$$

[20] As British soccer leagues operate a point-based system, the magnitude of a victory or a defeat has little influence on a club's position in league tables and future cash flows (see Section 5.3 for details). It is important to note that we also interacted *GoalDiff* with *Win* and *Loss*, respectively, and included the interaction terms in Eq. (7). These interaction terms are not statistically significant (Tables are available upon request). This is consistent with our expectation that investors do not value the margins of a victory or a defeat.

[21] As White's (1980) standard errors may be biased downward if the sample size is small, three versions of finite sample adjustments were proposed by MacKinnon and White (1985). Using MacKinnon and White's HC3 estimator of standard errors does not change our results.

[22] We also used an alternative measure of abnormal volume, i.e. the changes in the logarithms of volumes. Our results remain unchanged.

The numerator of AV(1,2) is the sum of the trading volumes on Monday and Tuesday. The denominator is the sum of trading volumes on Thursday and Friday. If AV(1,2) is positive (negative), it means that the cumulative trading volume on Monday and Tuesday is larger (smaller) than the cumulative trading volume on the preceding Thursday and Friday. However, it is possible that abnormal volume only captures a day-of-the-week effect independent of the game results. To control for this possibility, we test whether the average AV(1,2) around game dates is equal to the average AV(1,2) off season, i.e., in June and July.[23] The mean AV(1,2) around game dates and for the off-season period (June-July) are given in Table V, Panel A. Cumulated trading volumes on Monday and Tuesday are larger than cumulated trading volumes on Thursday and Friday, both around game dates and off-season. A test of the difference in means also shows that the mean abnormal volume around game dates is significantly larger (at the 5% level) than the mean abnormal volume for June and July.[24]

Taken together, Tables III to V show that investors react strongly to information contained in game results, and that share prices react faster to good news than to bad.

[Insert Table V about here]

5.2. Do the Market Reactions to Game Results Reflect Rational Expectations or an Overreaction?

The market reaction to the game results may reflect a rational reaction to news about the future cash flows of these listed firms or the quality of soccer players in these teams. For example, wins (losses) may have a direct economic impact on the club in terms of higher (lower) sales of related merchandise and advertising or the allocation of TV rights. As shown above, a win (a loss) generates average abnormal returns of about 1% (-1%) over the first three days for a given soccer club. As the average market capitalization of our sample firm over the period 1999-2002 is £62 million, one percent of the average market capitalization represents £0.6 million. This is comparable to the average sales revenue derived from a soccer game for a club.[25] Hence the value induced by the abnormal returns at the events is not unjustifiable by a change in discounted future

[23] Trading volume is available for 504 games (out of 916 games in our sample). We treat observations for which AV(1,2) is larger than 20 as outliers and remove them from our sample. We retain 475 AV(1,2) observations around games dates. For the AV(1,2) in June and July, we have 333 observations.

[24] Hong and Yu (2007) find that stock market turnover is significantly lower during the summer as market participants are on vacation. This should not bias our results as we use a difference-in-difference estimator to filter out the seasonality of trading volumes when comparing abnormal volumes during season with off-season. However, if the reduction of trading volumes in the summer also leads to a weaker day-of-the-week effect in volumes due to lack of trading activity, it is still possible that our tests of abnormal volume capture a day-of-the-week effect rather than reactions to game results.

[25] As the operating profits of listed soccer clubs are on average negative due to e.g. high fees paid to soccer players, we use total sales revenue to proxy for cash flows of a club. The average sales of a soccer club in our sample is £40 million per year, and a British clubs plays about 40 league matches in a soccer season. Hence, a soccer game on average generates about £1 million revenue for listed clubs in the UK.

cash flows triggered by the game. This simple calibration provides support for a rational explanation for the strong market reaction to game results. Furthermore, prior literature suggests that there is a positive relation between sports performance and profitability of sporting clubs. Brown and Hartzell (2001) document that the operating performance of US professional basketball, baseball and (American) football clubs is positively associated with teams' sports performance. Bernile and Lyandres (2008) also show that the profitability (measured as the ROA) of European soccer teams is increasing in sports performance. This suggests that soccer game results contain value-relevant information.

An alternative explanation is that soccer results influence stock returns through their impact on investor sentiment and/or information salience. For instance, stock markets may overreact to losses when soccer games generate a bad mood, especially when media coverage is omnipresent. We perform a number of tests to distinguish between the competing explanations for the market reaction to game results. First, we investigate whether the market reactions persist over time or are transitory. If investors overreact to game results, one would expect that the market reactions to game results are transitory and will disappear after a short period. We find that the abnormal returns following games tend to persist as the abnormal returns following wins are stronger over a five-day window than a two- or three-day window. Also, the fact that the sign of the average abnormal returns on day 1 is not reversed in days 2-5 suggests that investor reactions are not transitory. These findings either do not support the overreaction explanation, or indicate that the overreaction is not reversed in the short run (within a week after the game).[26]

Second, investor sentiment is more likely to influence the price of stocks disproportionately held by individual investors rather than that of stocks held by institutional investors (see e.g. Lee, Shleifer, and Thaler, 1991). We collect ownership data for the UK soccer clubs from the BvD/Amadeus database and partition our sample of soccer clubs into two mutually-exclusive groups based on the teams' ownership structure. The first group consists of seven teams whose blockholders (i.e. shareholders with at least a 3% stake) include at least one large institutional investor (i.e. mutual funds, investment trusts, financial institutions, etc.). These clubs are Celtic, Heart of Midlothian, Leeds United, Manchester United, Millwall, Newcastle United, and Preston North End. The second group consists of nine teams without such an institutional major shareholder. So, these teams have either no major blockholder (i.e. Charlton Athletic, Southampton, and Sheffield United) or a major non-institutional shareholder (i.e. a firm or an individual) (i.e. Aston Villa, Burnden Leisure (Bolton Wanderers), Birmingham City, Chelsea Village, Sunderland, and Tottenham Hotspur). The overreaction explanation predicts that the first type of teams experiences weaker price reactions to game results as institutional investors tend to be more rational

[26] It should be noted that this test is confined to a time frame of a week as soccer matches are played every weekend during the league competition. An event window longer than a week is contaminated by the high frequency of events.

than individual ones. However, we find that the second group has weaker market reactions, which does not support the overreaction explanation.

Third, while smaller stocks receive less media attention, they tend to be more strongly influenced by investor mood (Baker and Wurgler, 2006; Edmans et al., 2007). This helps us to distinguish between the competing explanations for the market reactions to game results. If the investor sentiment (information salience) hypothesis prevails, soccer results of smaller clubs should trigger stronger (weaker) price reactions. We partition our sample into two subsamples based on firm size. The group of small clubs includes eight firms (Bolton Wanderers, Birmingham City, Charlton Athletic, Heart of Midlothian, Millwall, Preston North End, Southampton, and Sheffield United). We find that the game results of the small clubs generate much stronger market reactions than those of large clubs. Following a win, the ACAR(0,3) is 1.2% for small clubs versus 0.6% for large clubs. For losses, the corresponding average abnormal returns are –1.3% and –0.6%. This result supports the conjecture that the market reaction to game results is driven by investor mood.[27]

Finally, if the market reactions reflect rational expectations on future firm value, investors would price the expected outcome of games before a game is played. Therefore, the market reactions to wins or losses should be weaker, the higher the probability of those outcomes. We partition our sample into subsamples based on the ex-ante expectations of games (derived from betting odds as explained in Sections 2 and 4.1) and the game outcomes[28], and show the results in Table VI. First, we find that the market reaction to a win is stronger the higher the probability of the win, which defeats the rational expectations hypothesis. For example, the ACAR(1,3) following a win is 1% when the win is strongly expected, whereas it is merely 0.5% when the team is strong expected to lose. This implies that investors overreact to a win, especially when the win was strongly expected (which should not have created a surprise effect). Second, consistent with our rational expectations hypothesis, the market reaction to a loss is weaker the higher its ex ante probability. For example, ACAR(1,3) following a loss is -1.3.% when the club was strongly expected to win (SEW), whereas it is merely -0.6% when the loss was strongly expected (SEL). Taking all this together, we find that the market reactions to wins cannot be explained by ex-ante expectations. This is at odds with the rational expectations explanation that the share price reactions to game results reflect the fact that investors update their expectations about future cash flows. In contrast, the market reactions to losses are consistent with investors' expectations. The asymmetric reaction to wins and losses (relative to ex-ante expectations) does not support the information salience explanation as both victories and defeats receive similar media coverage.

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[27] However, as smaller firms have a higher bid-ask spread, the result could also explained by the low liquidity of smaller firms.

[28] An alternative approach is to interact game outcomes (*Win* and *Loss*) with the ex-ante expectations of games (*Probwin*) and include the interaction terms in Eq. (7). We obtain similar results using this regression approach.

To conclude, we distinguished between competing explanations (rational expectations versus investor sentiment / information salience) for the market reactions to game outcomes. The results lead to nuanced conclusions. Consistent with the rational expectations explanation, sports performance is related to the operating performance of soccer clubs, and the value induced by the abnormal returns at the events is not unjustifiable by a change in discounted future cash flows triggered by the game. The market reactions to game outcomes are also not transitory in the short run. Firms with no institutional owners are not associated with stronger market reactions. However, smaller clubs experience stronger market reactions to game results. This implies that the market reaction may reflect investors' overreaction to the games induced by a shift in sentiment. When we relate the ex ante expectations to the market reaction, we obtain some interesting results: investors seem to overreact to a win, especially when the win is strongly expected ex-ante, due to positive sentiment. In contrast, when the teams lose, investors are less influenced by mood. Investors' loyalty to their clubs may lead to fewer share sales in the wake of bad news.[29]

[Insert Table VI about here]

5.3. Stock Price and Trading Volume Reactions to the Release of Betting Odds

Next, we examine whether the public information released by specialists (namely, the bookmakers' experts) by means of fixed odds is valuable. In other words, we examine whether betting odds on soccer games have some predictive power. Betting odds are translated into probabilities to win or lose as explained in Sections 2 and 4.1. 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 using binary probit models.

[Insert Table VII about here]

[29] Our results that investors overreact to wins rather than to losses in national soccer games are different from those of Edmans et al. (2007), who find a significant market decline after a country's losses in international soccer competitions. A potential explanation for the discrepancy is the different competition format between national and international soccer competitions. National league tables, e.g. the Premier League in England, are determined by the cumulative performance of a club (in terms of points gained) during a soccer season. For example, in British soccer league games, a club gains 3 points for a win, 1 point for a draw, and 0 points for a loss. Hence a win may have a larger impact on investor sentiment than a loss due to the inherent asymmetry in the point-based competition system. In contrast, in international competitions (e.g. the UEFA Champions' League) a loss can lead to an immediate removal of the team from the tournament.

Both Panels A and B of Table VII 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*) or a high probability difference (*ProbDiff*), as well as the teams which are strongly expected to win (*SEW*), do indeed win their games (models 1, 2, 4 and 5) and are able to avoid defeats (models 3 and 6). Likewise, the teams with betting odds strongly predicting a defeat (*SEL*) are indeed frequently defeated (as reflected by the positive coefficients in models 3 and 6) and rarely win (as indicated by the negative coefficients in models 1, 2, 4 and 5). All these results are highly statistically significant within the 0.1% level.

Panel A of Table VII 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 measure 'weakly expected to lose' using the somewhat more refined method of probability differences (*WEL[b]*), we find that teams that are weakly expected to lose, do indeed incur more defeats and realise fewer victories (Panel B). Still, the magnitude of the parameter coefficients as well as their statistical significance are lower than those of teams with betting odds reflecting strong predictions of victories or defeats. Thus, a higher degree of uncertainty in the betting odds does indeed reflect the higher uncertainty of the team's performance on the field. We conclude that betting odds are very good predictors of the game outcomes. Our results are consistent with the existing literature on betting markets (see Sauer (1998) for a review).

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 investors are rational and the odds contain new information. The above should be fulfilled according to Bayes' rule. Panel A of Table VIII exhibits the ACARs over the two days prior to the game (Thursday and Friday). Interestingly, we find neither an economic nor a statistically significant price reaction to the posting of betting odds.

The absence of a price reaction does not necessarily mean that the investors ignore the information contained in odds. It may be the case that investors have heterogeneous interpretations of public information. In that case, abnormal trading volumes could be observed (in the absence of price movements) if information is processed by investors (see Kandel and Pearson, 1995).

To capture abnormal trading volumes, we use the following measure:

$$\text{AV(-2, -1)} = \frac{\text{Volume}\,(t = -2) + \text{Volume}\,(t = -1)}{2 * \text{Volume}\,(t = -3)} - 1$$

The numerator of AV(-2,-1) is the sum of the trading volumes on Thursday and Friday. The denominator is twice the trading volume on Wednesday. If AV(-2,-1) is positive (negative), the average trading volume on Thursday and Friday is larger (smaller) than the trading volume on Wednesday. As in the case of the volume reaction to game results, we control for the possibility of a day-of-the-week effect by comparing the AV(-2,-1) after the release of the fixed odds, with the off-season AV(-2,-1) (i.e., the abnormal volume in June and July). The results are shown in Panel B of Table VIII. We do not find any evidence that there is a difference between the average abnormal volumes after the release of odds during the soccer season and the average abnormal trading volume during the off-season.

[Insert Tables VIII and IX about here]

We test the stock price reactions to betting odds 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 IX. We observe that none of the estimated coefficients of these expectation dummies is significantly different from zero. This result provides additional evidence that investors do not react to betting odds.

5.4. Can Betting Odds Predict Stock Returns? The Impact of Information Salience and Investor Mood

There may be several explanations for the lack of a market reaction to the release of the betting odds although they are excellent predictors of the game outcomes. The first explanation is that betting odds do not contain any new information that has not yet been incorporated into the prices. The second explanation is that investors neglect information conveyed by betting odds due to low salience levels or high transaction costs. Game results are available on a wider scale and may even be even hard to avoid: they are presented in all daily newspapers, in the television and radio news, and in various sports TV programs in prime time. Conversely, betting odds are available only on bookmakers' websites, in specialized sports publications, or in betting offices. Hence, some public information with low media coverage (salience) may not be picked up by investors.

To find out which of the two explanations prevails, we investigate whether or not betting odds have some predictive power for future stock returns. If the odds do predict returns, it follows that the market neglects information contained in odds. Formally, to test the predictive power of fixed odds on stock returns, we compute the *ACARs* conditional on the strength of the experts' predictions as reflected in the betting odds (*SEL, WEL, WEW, SEW*). Table X provides the results for several time horizons. In particular, we observe in Panel A that for teams strongly expected to win under specification [a] (i.e., using *ProbWin*), the three-day average abnormal return is 61.37 basis points (significantly positive at the 1% level). Using specification [b] (i.e., based on *Probdiff*), the three-day reaction is somewhat larger (64.10 basis points, significantly positive at the 5% level). We also examine a naïve trading strategy that extends over 60 trading days: an investor buys a share in a firm that is strongly expected to win and sells the share after 3 months regardless of the intermediate news on the team's performance. Panel B of Table X shows that this naïve trading rule generates between 175 and 245 basis points (depending on the probability measure *Probdiff* and *ProbWin*, respectively) on average over and above the expected returns. In contrast to the rational expectations hypothesis, these results suggest that betting odds contain unpriced information to investors.

We also test the relation between the prediction of the game results (the betting odds) and the market price reaction subsequent to the game by running the following OLS regressions (of which the variables are defined above):

$$CAR(1,j) = \alpha_0 + \alpha_1 SEW[i] + \alpha_2 WEL[i] + \alpha_3 SEL[i] + \beta ControlVariables + \varepsilon,$$
$$(i=a,b,\ j=2,3) \qquad (15)$$

Table XI confirms the results of Table X. Under both specifications [a] and [b], *SEW* is statistically significantly related to the various *CARs* in the four regressions.

[Insert Tables X and XI about here]

One may reach the conclusion that betting odds predict stock returns and that investors ignore non-salient information. Still, an alternative explanation is that a trading strategy based on betting odds may be unprofitable after taking into account the transaction costs. As discussed in Section 3, listed soccer clubs tend to be small firms with low trading liquidity. For example, the median bid-ask spread (defined as the difference between the bid and ask prices at the closing time divided by the average of the bid and ask prices) of these stocks in our sample period ranges from 1.6% for the most liquid firm (Manchester United) to 15.4% for the least liquid stock (Sheffield United). Hence it is questionable whether investors can take advantage of the information in betting odds prior to the games. If investors are not able to exploit the potential trading profits, our results do not necessarily support the information salience hypothesis which states that investors underreact to the less salient information, namely that conveyed by the betting odds. Furthermore, given that both victories and defeats receive similar media coverage and odds are good predictors of game outcomes, the odds should predict stock returns for *both* expected-to-win *and* expected-to-lose teams. However, we find that odds only predict the stock returns well for strongly-expected-to-win games. Therefore, information salience is here a less credible explanation for our results as there is no reason why the information salience hypothesis would be asymmetric (be valid for losses but not for wins).

As investors' reactions to soccer results could be driven by mood (Edmans et al., 2007), we investigate whether this sentiment can explain the predictive power of fixed odds for stock returns before transaction costs. As shown in Section 5.2, investors' reaction to a win, in contrast to the market reaction to a loss, is not consistent with the expectations about the games' outcomes. In particular, investors overreact to wins which are ex ante strongly expected to occur and which should not have triggered a strong surprise effect. This is in line with our finding: if teams are strongly expected to win, fixed odds predict post-game abnormal returns, while this is not the case if teams are strongly expected to lose. Hence, we believe that the main explanation for the results presented in this section is related to investor sentiment.

6. Robustness of the Findings

6.1. 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 4.1, our results remain qualitatively equivalent when we choose 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.

6.2. Liquidity of stocks and timing of games

We also verify whether our results are driven by a few small firms with low liquidity in the trading of their shares. In all regressions, we control for team-specific effects by using team dummies. In addition, if we drop the smaller clubs from our sample, our main results still hold.

Furthermore, game outcomes may become more important to investors near the end of the season when the competition becomes 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.

6.3. Econometric Issues (ARMA models, bootstrapping, clustered standard errors)

First, given the low liquidity of some of the stocks in this study, the closing price may bounce between the bid and ask prices. This may generate a negative autocorrelation in returns and bias our statistical inference. However, this effect does not affect our results. After adjusting for autocorrelation in stock returns, our results (both the coefficients and the significance levels) are unchanged. More specifically, following Brown and Hartzell's (2001: 366) methodology (i.e., verifying the autocorrelation by means of an AR(1) model and a MA(1) model), we check the autocorrelations by using the residuals from an ARMA(1,1) model as abnormal returns. The ARMA(1,1) model we consider is:

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

where $\varepsilon_{i,t}$ is the abnormal returns, $\lambda r_{i,t-1}$ represents the autoregressive process (AR) in raw returns, and $\eta\varepsilon_{i,t-1}$ represents the moving average process (MA) in residuals. Thus, under the assumption that stock returns follow a ARMA(1,1) process, the abnormal returns ($\varepsilon_{i,t}$) follow a random walk. We rerun all the regressions discussed in this paper using the residuals from the ARMA(1,1) model as abnormal returns. The results remain largely unchanged and are available upon request.

Second, as we have only performed OLS regressions, one may argue that if the residuals of regressions are not normally distributed, the statistical inference from the t-test may be biased. We use a bootstrap method to obtain the empirical distribution of the estimated coefficients of the OLS regressions. The procedure has three main steps. First, we resample data by randomly drawing (with replacement) the residuals of OLS regressions from our sample. For one completed draw of regression residuals, we calculate the bootstrapped values of the dependant variables. Second, once the bootstrapped data has been created, we run regressions on the resampled data to estimate the coefficients of the explanatory variables. Third, we repeat the above steps 150 times to generate a distribution of the estimates.[30] From this distribution we compute the empirical p-values of the estimated coefficients in the regressions. Our main results remain unchanged.

Third, we also control for heteroskedasticity and potential dependence in residuals of regressions. In particular, using White standard errors in the regressions or employing clustered standards errors by firm does not change our results.

7. Conclusions

We started off asking the question whether or not the stock market incorporates the news of victories, defeats and draws of listed British soccer clubs. The average cumulative abnormal returns over a three day period are strongly statistically significant and amount to 88 basis points for a victory, -101 basis points for a defeat, and -33 basis points for a draw. We also find that markets are very fast in processing good news about game outcomes (most of the impact of a victory is incorporated in the share prices during the first trading day) and somewhat slower in incorporating bad news (defeats). On the first trading day following a game, we observe significant share volume increases.

A second question emerges as to whether these market reactions reflect rational expectations (as the previous literature shows a relation between game outcomes and future operating performance) or the abnormal returns can be explained by investor sentiment or information salience. While the weekly value changes represented by the abnormal returns are not unjustifiable by the potential change in discounted cash flows, we find evidence of investor overreaction

[30] When we increase the size of simulations to 1000 samples, the significance levels of estimated coefficients do not change.

following the game outcomes. We apply several tests to study investor mood and information salience: Are the abnormal returns transitory? Are smaller firms and firms with no institutional owners more prone to overreaction? Are the market reactions to wins or losses weaker, the higher the ex ante probability of those outcomes? Our most convincing test gives evidence that investors overreact to a win, especially when the win was strongly expected and hence should not have created a surprise effect. Investor sentiment also causes an asymmetric share price reaction: wins trigger abnormal returns due to a positive sentiment, but, consistent with the rational expectations hypothesis, the market reaction to a loss is weaker the higher its ex ante probability. Investors' loyalty to their clubs may lead to fewer share sales in the wake of bad news.

Our third question is about how the market receives the experts' opinions about the probability of the game outcomes. These opinions are embedded in the betting information (fixed odds) which is released some days prior to the games. We do not find any significant reaction (neither in share prices nor in trading volumes) to the release of betting odds by bookmakers. This is particularly interesting as we show that the betting odds are excellent predictors of the game outcomes. It is now widely acknowledged that individuals have limited information processing abilities. One of the consequences is that the way information is processed may depend on its relative salience, i.e., the media coverage it receives. Professional soccer clubs listed on the London Stock Exchange provide a unique way of studying stock price reactions to different types of news since two pieces of news are released on a weekly basis from August to June: betting odds which incorporate information about the expected future performance, and game results which capture information about the realized performance. Furthermore, these two types of information differ in their level of salience: game results receive very high media coverage (in all daily newspapers, in the television news, and in sports shows on prime time), while betting odds are only posted on bookmakers' websites, in specialized sports magazines and in betting shops. In contrast to the significant volume and share price reaction subsequent to the game results, there is none subsequent to the release of the betting odds. This may be due to the fact that the latter information is not salient. Still, some caution is needed with this interpretation as it may be that the odds do not contain any new information that has not yet been incorporated into stock prices. Also, the bid-ask spreads of the listed soccer clubs (which are mostly small caps) are high such that developing a profitable trading strategy may be difficult.

Due to the absence of a market reaction to the disclosure of betting odds, we ask our fourth question: can betting odds be used to predict short-run market returns? Formally, to test the predictive power of fixed odds on stock returns, we compute the *ACARs* conditional on the strength of the experts' predictions as reflected in the betting odds (strongly expected to win, weakly expected to win, weakly expected to lose, strongly expected to lose). In particular, we observe that the 3-day (statistically significant) average abnormal return is 64 basis points subsequent to the game outcome when the team was strongly expected to win. This suggests that betting odds contain new information to investors (which does not support the rational expectations hypothesis). A naïve 60-day trading strategy whereby an investor buys a share in a firm that is strongly expected to win and sells after 3 months (regardless of the intermediate news) yields on average between 175 and 245 basis points over and above the expected returns. However, the potential trading profits largely disappear when transaction costs are taken into account. Remarkable is that significant abnormal returns only emerge when teams are strongly expected to win and not when teams are weakly expected to win or strongly expected to lose. The asymmetric predictability of betting odds to stock returns following wins and losses and the fact that there is still a market reaction when the outcome is most anticipated, does not support the information salience hypothesis but leads to our conclusion that investor sentiment influences the news absorption by the stock market.

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Table I
Soccer clubs and sporting performance

This table presents the soccer clubs included in our sample and gives their positions in their leagues for the 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 the average market value for the period 1999-2002, in GBP million. 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 seasons in 2000, 2001 and 2002.

Club	List Date	Exchange	MV (£ million)	League & Position 1999-00		2000-01		2001-02	
Aston Villa	April 1997	LSE	36.5	EP	6	EP	8	EP	8
Burnden Leisure (Bolton Wanderers)	April 1997	AIM	13.1	E1	6	E1	3	EP	16
Birmingham City	March 1997	AIM	17.3	E1	5	E1	5	E1	5
Chelsea Village	March 1996	AIM	76.2	EP	5	EP	6	EP	6
Celtic	Sept. 1995	LSE	50.1	SP	2	SP	1	SP	1
Charlton Athletic	March 1997	AIM	16.9	E1	1	EP	9	EP	14
Heart of Midlothian	May 1997	LSE	9.1	SP	3	SP	5	SP	6
Leeds United	Aug. 1996	LSE	48.6	EP	3	EP	4	EP	5
Manchester United	June 1991	LSE	516.9	EP	1	EP	1	EP	3
Millwall	Jan. 1989	LSE	16.8	E2	5	E2	1	E1	4
Newcastle United	April 1997	LSE	70.4	EP	11	EP	11	EP	4
Preston North End	Jan. 1995	AIM	6.8	E2	1	E1	4	E1	8
Southampton	Jan. 1997	LSE	12.3	EP	15	EP	10	EP	11
Sunderland	Dec. 1996	LSE	33.7	EP	7	EP	7	EP	17
Sheffield United	Dec. 1996	LSE	5.8	E1	16	E1	10	E1	13
Tottenham Hotspur	Jan. 1983	LSE	53.9	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) of the listed soccer clubs. The percentages of total sales derived from soccer related activities are reported for 2002. The summary statistics are calculated across firms. 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 Leisure (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	42.0	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	116.0	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	0.0
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	46.0	43.8	100%	-6.9	1.6	-7.8
Sheffield United	5.8	6.5	10.0	97%	-5.0	-3.6	-2.4
Tottenham Hotspur	48.0	48.4	65.0	100%	-4.2	-1.7	-4.8
Mean	35.2	40.7	49.0	94%	-3.8	-2.7	-4.4
St. Dev	34.4	36.0	39.8	11%	6.8	6.9	8.9
Median	28.3	34.3	41.2	100%	-4.1	-3.1	-3.0

Table III
Market reactions to game results

This table presents the average (cumulative) abnormal returns (A(C)ARs) in basis points subsequent to the soccer games. Panel B and Panel C show the A(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 A(C)ARs, respectively.

	N	Reaction to games		
		AAR(1)	ACAR(1,2)	ACAR(1,3)
Panel A:	*All games*			
Win	405	52.72	63.45	88.26
p-value of t-test		(0.000)	(0.000)	(0.000)
p-value Wilcoxon		(0.000)	(0.000)	(0.000)
Draw	233	-8.15	-25.01	-32.54
p-value of t-test		(0.652)	(0.367)	(0.281)
p-value Wilcoxon		(0.337)	(0.457)	(0.727)
Loss	278	-27.95	-57.02	-100.81
p-value of t-test		(0.011)	(0.000)	(0.000)
p-value Wilcoxon		(0.095)	(0.003)	(0.000)
Panel B:	*Games in August-March*			
Win	329	51.46	65.16	81.09
p-value of t-test		(0.001)	(0.000)	(0.000)
p-value Wilcoxon		(0.000)	(0.000)	(0.000)
Draw	187	-0.64	-9.82	-17.72
p-value of t-test		(0.974)	(0.748)	(0.591)
p-value Wilcoxon		(0.436)	(0.497)	(0.799)
Loss	222	-21.10	-54.22	-102.66
p-value of t-test		(0.063)	(0.003)	(0.000)
p-value Wilcoxon		(0.163)	(0.006)	(0.006)
Panel C:	*Games in April-June*			
Win	76	58.17	56.02	119.30
p-value of t-test		(0.051)	(0.186)	(0.041)
p-value Wilcoxon		(0.222)	(0.175)	(0.047)
Draw	46	-38.68	-86.78	-92.80
p-value of t-test		(0.381)	(0.187)	(0.211)
p-value Wilcoxon		(0.544)	(0.714)	(0.789)
Loss	56	-55.10	-68.11	-93.48
p-value of t-test		(0.081)	(0.052)	(0.031)
p-value Wilcoxon		(0.344)	(0.154)	(0.370)

Table IV
Market reactions to game results: regression results

This table presents the OLS regression results explaining the cumulative abnormal returns (CARs) following the soccer games. The dependent variables are the announcement abnormal return and the CAR(1,2) and CAR(1,3). *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. ***, **, * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

Dep. Variable :	AR(1)	AR(1)	CAR(1,2)	CAR(1,2)	CAR(1,3)	CAR(1,3)
Constant	23.40	4.46	-7.35	-22.50	-42.12	-45.87
	(0.924)	(0.986)	(0.983)	(0.948)	(0.921)	(0.914)
GoalDiff	18.91***		26.22***		37.85***	
	(0.000)		(0.000)		(0.000)	
Win		58.94***		83.16***		119.39***
		(0.004)		(0.004)		(0.001)
Loss		-19.20		-35.08		-65.02*
		(0.388)		(0.254)		(0.087)
PostMarch	-16.28	-16.98	-29.21	-29.89	-1.40	-1.99
	(0.432)	(0.412)	(0.309)	(0.297)	(0.969)	(0.955)
AIM	-29.06	-29.03	-53.35	-60.95	-63.13	-85.35
	(0.907)	(0.907)	(0.876)	(0.859)	(0.882)	(0.840)
Home	-5.77	-4.28	0.77	0.95	34.98	32.62
	(0.730)	(0.797)	(0.974)	(0.967)	(0.224)	(0.252)
Cup	-18.06	-18.54	6.19	5.87	-5.39	-5.12
	(0.536)	(0.526)	(0.878)	(0.885)	(0.914)	(0.918)
Year9900	20.18	19.02	59.03**	56.63**	82.84**	78.27**
	(0.321)	(0.350)	(0.037)	(0.045)	(0.018)	(0.025)
Year0001	27.79	26.11	57.37**	54.56*	79.65**	75.00**
	(0.174)	(0.202)	(0.043)	(0.054)	(0.023)	(0.032)
Team Dummies	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.044	0.045	0.045	0.049	0.050	0.060
F-Statistics	1.85***	1.83***	1.91***	2.00***	2.15***	2.46***
Prob > F	0.010	0.010	0.007	0.004	0.002	0.000

Table V
Trading volume reactions to game results

Panel A of this table presents the average abnormal volumes (AAVs) in percentage subsequent to the soccer games. 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 AAVs, respectively. Panel B presents the OLS regression results explaining the abnormal volumes following soccer games. The dependent variables are AV(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 475 observations. ***, **, * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Average Trading volume reactions

	N	Reaction to games	N	June-July	Difference
AAV(1,2)	475	121.21%	333	89.4%	31.81%
p-value of t-test		(0.000)		(0.000)	(0.025)
p-value Wilcoxon		(0.000)		(0.000)	(0.013)

Panel B: Regression results

Dep. Variable :	AV(1,2)	AV(1,2)
Constant	21.08	14.38
	(0.944)	(0.962)
GoalDiff	12.82	
	(0.116)	
Win		21.40
		(0.538)
Loss		-23.50
		(0.539)
PostMarch	10.12	9.91
	(0.744)	(0.749)
AIM	169.11	176.86
	(0.598)	(0.583)
Home	15.62	19.37
	(0.584)	(0.493)
Cup	84.84*	87.66*
	(0.075)	(0.067)
Year9900	-8.56	-7.75
	(0.820)	(0.838)
Year0001	15.09	15.08
	(0.696)	(0.698)
Team Dummies	Yes	Yes
R^2	0.075	0.073
F-Statistics	1.74**	1.63**
Prob > F	0.018	0.032

Table VI
Market reactions to game results conditional on ex ante expectations

This table presents the average cumulative abnormal returns (ACARs) in basis points subsequent to wins, draws and losses, categorized on the basis of the betting odds. We define 4 dummy variables which indicate whether a team was strongly expected to win *(SEW),* weakly expected to win (*WEW),* weakly expected to lose *(WEL,) or* strongly expected to lose *(SEL).* We label the above variables by [a] (when *ProbWin* is used*)* in Panel A and by [b] (when *Probdiff* is used) in Panel B. The p-values (in parentheses) of the t-test and the Wilcoxon signed-rank test are presented in the first and second rows underneath the ACARs, respectively.

Panel A	*Specification [a]*				
		SEW[a]	WEW[a]	WEL[a]	SEL[a]
Win	ACAR(1,3)	104.6	83.44	50.52	49.46
	p-value of t-test	(0.000)	(0.081)	(0.312)	(0.546)
	p-value Wilcoxon	(0.000)	(0.069)	(0.091)	(0.065)
	Number of observations	232	84	63	26
Draw	ACAR(1,3)	37.79	-129.83	-59.14	41.34
	p-value of t-test	(0.314)	(0.043)	(0.422)	(0.604)
	p-value Wilcoxon	(0.185)	(0.138)	(0.396)	(0.627)
	Number of observations	82	66	56	29
Loss	ACAR(1,3)	-126.92	-120.83	-117.77	-59.05
	p-value of t-test	(0.025)	(0.010)	(0.033)	(0.030)
	p-value Wilcoxon	(0.054)	(0.089)	(0.081)	(0.098)
	Number of observations	43	77	67	91

Panel B	*Specification [b]*				
		SEW[b]	WEW[b]	WEL[b]	SEL[b]
Win	ACAR(1,3)	102.3	89.48	64.49	29.96
	p-value of t-test	(0.002)	(0.023)	(0.133)	(0.834)
	p-value Wilcoxon	(0.004)	(0.004)	(0.022)	(0.256)
	Number of observations	185	126	79	15
Draw	ACAR(1,3)	44.47	-83.64	-68.87	90.29
	p-value of t-test	(0.409)	(0.092)	(0.265)	(0.306)
	p-value Wilcoxon	(0.504)	(0.470)	(0.690)	(0.322)
	Number of observations	56	83	73	21
Loss	ACAR(1,3)	-134.8	-124.25	-113.56	-49.82
	p-value of t-test	(0.016)	(0.010)	(0.010)	(0.091)
	p-value Wilcoxon	(0.040)	(0.090)	(0.087)	(0.261)
	Number of observations	30	80	89	79

Table VII
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 the probability measure 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 regressions are used when the dependent variable is *GoalDiff*, and probit regressions when *Win* and *Loss* are the dependent variables. The p-values of the estimated coefficients are in parentheses. All regressions have 916 observations. ***, **, * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

Quality of odds [a]	Model 1		Model 2		Model 3	
	Ordered probit		Probit		Probit	
Dependent Var.:	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 VII continues on the next page.

Table VII – Continued

Quality of odds [b]	Model 4		Model 5		Model 6	
	Ordered probit		Probit		Probit	
Dependent Var.:	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)		(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 VIII
Market reactions to odds

This table presents the (cumulative) average abnormal returns ((C)AARs) in basis points (in Panel A) and the average abnormal volumes (AAVs) in percentage (in Panel B) 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 the probability measure 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 (volumes). The p-value of the Wilcoxon rank-sum test is presented in the second row following the difference in abnormal volumes between on- and off-seasons.

Panel A: Stock price reactions to betting odds

	N	Reaction to odds [a]			N	Reaction to odds [b]		
		AAR(-2)	AAR(-1)	ACAR(-2,-1)		AAR(-2)	AAR(-1)	ACAR(-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)

Panel B: Trading volume reactions to betting odds

	N	Reaction to odds	N	June-July	Difference
AAV(-2,-1)	475	139.08%	324	128.91%	10.17%
p-value of t-test		(0.000)		(0.000)	(0.540)
p-value Wilcoxon		(0.000)		(0.000)	(0.451)

Table IX
Market reactions to odds: regression results

This table presents the OLS regression results explaining the cumulative abnormal returns (CARs) immediately after the betting odds are posted. The dependent variables are the 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 the probability measure 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 X
Predictability of betting odds

This table presents the (cumulative) average abnormal returns ((C)AARs) 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 the probability measure 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, respectively, following the ACARs. In Panel B, the p-values of the t-test are computed using Newey-West standard errors of the time-series of average CARs to account for serial correlation. The naïve trading rule of Panel B works as follows. Every week, an investor buys a share in firms strongly (weakly) expected to win or to lose. The investor adopts this naïve buy-and-hold strategy for 3 months when he takes the opposite position; he does not take into account intermediate news to change his position. Every week, he repeats this strategy.

Panel A: Short-run predictability

	Specification [a]			Specification [b]		
	N	ACAR(1,2)	ACAR(1,3)	N	ACAR(1,2)	ACAR(1,3)
SEW	357	43.81	61.37	271	50.02	64.10
p-value of t-test		(0.010)	(0.005)		(0.020)	(0.013)
p-value Wilcoxon		(0.010)	(0.005)		(0.031)	(0.040)
WEW	227	-29.76	-47.86	289	-15.86	-19.40
p-value of t-test		(0.188)	(0.115)		(0.380)	(0.459)
p-value Wilcoxon		(0.724)	(0.474)		(0.682)	(0.618)
WEL	186	-25.74	-43.12	241	-24.12	-41.65
p-value of t-test		(0.381)	(0.207)		(0.326)	(0.144)
p-value Wilcoxon		(0.697)	(0.621)		(0.779)	(0.680)
SEL	146	-0.56	-19.79	115	7.46	-13.83
p-value of t-test		(0.982)	(0.466)		(0.798)	(0.659)
p-value Wilcoxon		(0.918)	(0.700)		(0.865)	(0.659)

Panel B: A naive long-run trading rule

	Specification [a]			Specification [b]		
	N	ACAR(1,10)	ACAR(1,60)	N	ACAR(1,10)	ACAR(1,60)
SEW	357	126.10	245.11	271	102.69	175.43
p-value of t-test		(0.009)	(0.045)		(0.092)	(0.056)
p-value Wilcoxon		(0.011)	(0.054)		(0.082)	(0.081)
WEW	227	-106.69	-119.49	289	-4.74	97.08
p-value of t-test		(0.081)	(0.342)		(0.921)	(0.572)
p-value Wilcoxon		(0.112)	(0.331)		(0.557)	(0.845)
WEL	186	-19.99	-46.10	241	-55.24	-113.29
p-value of t-test		(0.704)	(0.604)		(0.181)	(0.223)
p-value Wilcoxon		(0.849)	(0.440)		(0.275)	(0.216)
SEL	146	32.44	-53.07	115	75.39	-36.80
p-value of t-test		(0.635)	(0.762)		(0.181)	(0.823)
p-value Wilcoxon		(0.589)	(0.471)		(0.414)	(0.645)

Table XI
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) and CAR(1,3). 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 the probability measure 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. ***, **, * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

	Specification [a]		Specification [b]	
	CAR(1,2)	CAR(1,3)	CAR(1,2)	CAR(1,3)
Constant	-130.58	-214.10	-127.83	-199.99
	(0.704)	(0.616)	(0.710)	(0.640)
SEW	81.19**	109.94***	70.65**	82.28**
	(0.014)	(0.007)	(0.033)	(0.045)
WEL	1.49	5.67	-7.66	-13.87
	(0.966)	(0.897)	(0.812)	(0.729)
SEL	36.04	37.61	28.10	16.98
	(0.353)	(0.435)	(0.495)	(0.740)
PostMarch	-32.94	-6.59	-32.38	-5.97
	(0.254)	(0.854)	(0.263)	(0.868)
AIM	43.60	72.91	49.05	74.56
	(0.899)	(0.865)	(0.887)	(0.862)
Home	-9.71	20.93	-5.02	30.04
	(0.737)	(0.560)	(0.864)	(0.409)
Cup	-3.68	-18.12	-3.73	-16.18
	(0.928)	(0.722)	(0.928)	(0.751)
Year9900	59.10**	83.23**	62.20**	87.68**
	(0.039)	(0.019)	(0.029)	(0.013)
Year0001	57.92**	80.12**	59.07**	82.66**
	(0.043)	(0.025)	(0.039)	(0.020)
Team Dummies	Yes	Yes	Yes	Yes
R^2	0.036	0.036	0.034	0.033
F-Statistics	1.38*	1.39*	1.32	1.25
Prob > F	0.10	0.10	0.14	0.19