Understanding Investor Sentiment: The Case of Soccer*

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Abstract

We examine two potential explanations for instances of stock market's inefficient responses to resolutions of uncertainty: a) biased *ex-ante* beliefs regarding probability distributions of possible event outcomes, and b) irrational *ex-post* reactions to the outcomes. We use a sample of publicly traded European soccer clubs and analyze their returns around important matches. Using a novel proxy for investors' expectations based on contracts traded on betting exchanges (prediction markets), we find that within our sample investor sentiment is attributable largely to a systematic bias in investors' ex-ante expectations. Investors are overly optimistic about their teams' prospects ex-ante and, on average, end up disappointed ex-post, leading to negative post-game abnormal returns. Our evidence is not entirely consistent with investors reacting irrationally to game results. Our results may have important implications for firms' investment decisions and corporate control transactions.

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1 Introduction

What is investor sentiment? Defined very broadly, investor sentiment is present whenever security prices deviate from present values of future cash flows. There are two potential reasons for such deviations. First, investors may incorporate considerations that are due to behavioral biases or emotions while evaluating securities (see Hirshleifer (2001) for an excellent overview of psychological biases and Saunders (1993), Hirshleifer and Shumway (2003), Kamstra, Kramer and Levi (2000, 2003), Frieder and Subrahmanyam (2004), and Yuan, Zheng and Zhu (2005) for examples of the effects of these biases on stock prices). Second, investors may have biased estimates of future cash flows or their distributions (e.g., Baker and Wurgler (2006, 2007)). In this paper we attempt to disentangle the two sources of investor sentiment and examine their effects on stock returns.

The distinction between the two manifestations of investor sentiment is important. Consider firms' earnings announcement as an example. Skinner and Sloan (2002) and Trueman, Wong and Zhang (2003) find that growth firms, and internet firms in particular, respond asymmetrically to earnings announcements. Specifically, average realized negative return following negative earnings surprises is significantly larger in magnitude than mean positive return following positive surprises. There are two potential interpretations of this result. First, investors may have overly optimistic expectations of firms' earnings, resulting in average negative return following earnings announcements. Second, investors may have unbiased beliefs regarding the distribution of earnings but may react irrationally to earnings surprises, this ex-post irrational reaction not being incorporated into pre-announcement stock prices.

Under the first scenario, referred to as "immediate emotions" (see Loewenstein (2000)), firms' post-announcement market values are efficient, while pre-announcement values are inefficient. Under the second scenario, referred to as "anticipated emotions", pre-event stock prices are efficient, and post-event ones are not. Many of firms' important decisions are based in part on their efficient market values. Examples include real investments (e.g., Tobin (1969), Hayashi (1982)), timing of mergers and acquisitions (e.g., Hackbarth and Morellec (2008)), and corporate control decisions in general (e.g., Shleifer and Vishny

(1986)).[1] Thus, understanding the evolution of stock prices around resolutions of uncertainty is crucial for firm value maximization.

In order to disentangle the two potential investor-sentiment-based effects and examine the effects of investors' potential ex-ante inability to correctly estimate event outcomes and of possible (irrational) emotional ex-post reactions on stock returns, we focus on the stock price behavior of publicly traded sports clubs. Stock prices of sports franchises provide a unique setting for examining the sources of investor sentiment for two reasons. First, frequent, easily quantifiable, and value-relevant information signals have observable ex-ante (objective) expectations (e.g., Brown and Hartzell (2001)). Second, sporting events constitute an ideal setting for testing the effects of emotional reactions to event outcomes, as demonstrated by Edmans, Garcia and Norli (2007). Introducing a proxy for investors' (subjective) beliefs regarding the probabilities of potential game outcomes enables us to estimate the portion of inefficient post-game returns that is attributable to differences in investors' subjective expectations and objective probabilities of match outcomes. We attribute the unexplained portion of returns to investors' irrational reaction to game results.

We show that, in our context, sentiment is largely an ex-ante phenomenon, as investors' beliefs about the likelihoods of possible realizations of uncertainty are biased. Specifically, investors are overly optimistic ex-ante and, thus, typically end up disappointed ex-post. Our results are not entirely consistent with the idea that investors' reactions to results of soccer matches are irrational.

Our study is related to the seminal work of Brown and Hartzell (2001), as well as papers by Palomino, Renneboog and Zhang (2005) and Renneboog and Van Brabant (2000) in that we analyze stock returns of sports franchises. Brown and Hartzell examine the returns of the Boston Celtics Limited Partnership following Boston Celtics basketball games. Palomino, Renneboog and Zhang, and Renneboog and Van Brabant concentrate on the returns of British publicly traded soccer clubs. Consistent with the latter studies, we document a significant mean positive return after wins and a significant mean negative return after

[1] Inefficient market values can also affect corporate decisions, such as overvaluation-driven acquisisions in Shleifer and Vishny (2003).

losses. Importantly, similar to Brown and Hartzell (2001) and to Edmans, Garcia and Norli (2007) we find that the overall mean post-game return is negative. The market's reaction to game outcomes is asymmetric: stock price changes following losses are substantially larger in magnitude than those following wins.

We use a novel proxy for investors' ex-ante beliefs about game outcomes, which, to the best of our knowledge, has not been used before. Proxies for objective probabilities of match outcomes used in the existing literature (e.g., Brown and Hartzell (2001), Palomino, Renneboog and Zhang (2005), and Edmans, Garcia and Norli (2007)) include bookmaker odds and/or predicted in-sample probabilities of wins, losses, and draws. Bookmaker odds are generally found to be efficient predictors of game outcomes (e.g., Sauer (1998)).[2] Yet, anecdotal evidence suggests that soccer fans grossly overestimate their teams' chances of success (see Edmans, Garcia and Norli (2007)). Moreover, bookmakers are reportedly more skilled at predicting game outcomes than bettors and, thus, quote odds that deviate systematically from bettors' expectations (e.g., Levitt (2004)). Finally, investors appear to ignore the periodic release of bookmaker odds (e.g., Palomino, Renneboog and Zhang (2005)). Therefore, it is not clear to what extent bookmaker odds, compiled by a small group of experts (forecasters), or in-sample fitted values reflect investors' subjective beliefs, which are expected to affect clubs' post-game stock returns through the uncertainty resolution component.

We argue that a better – albeit far from perfect – proxy for investors' subjective expectations of game outcomes is the market price of related contracts that are traded on betting exchanges (prediction markets).[3] The crucial difference between prices set in a betting exchange and bookmaker odds is that the former are determined by investors' demand for and supply of underlying contracts, whereas bookmakers post odds and take sides in each transaction. Thus, the odds quoted by bookmakers represent the expectations of "bet compilers" and do not necessarily correspond to the subjective beliefs of investors in

[2] We discuss the efficiency of odds in predicting game results in Section 5.

[3] See Wolfers and Zitzewitz (2003) for a discussion of betting exchanges or "prediction markets". See Arrow et al. (2007) for a statement that encourages U.S. regulators to lower the barriers to creating new prediction markets, arguing that they provide superior forecasting tools.

soccer stocks. We argue that equilibrium prices of contracts traded in prediction markets are better aligned with investors' beliefs.[4]

Our analysis of betting exchange prices also contributes to the literature examining the efficiency of betting markets (e.g., Golec and Tamarkin (1991), Gray and Gray (1997), Palomino, Renneboog and Zhang (2005), Sauer, Brajer, Ferris and Marr (1988), Vlastakis, Dotsis and Markellos (2006), and Zuber, Gandar and Bowers (1985) among many others). Consistent with anecdotal evidence, our empirical tests show that there are systematic differences between betting exchange prices and bookmaker odds. In particular, betting exchange prices typically reflect an overly optimistic assessment of public teams' prospects. Interestingly, both the types of inefficiencies and their magnitudes differ between bookmaker odds and betting exchange prices. For instance, teams playing away from home are overvalued on betting exchanges, as the in-sample proportion of wins by away teams is significantly lower than the prices of the corresponding contracts would imply, whereas no such bias is evident in bookmaker odds.

Our tests show that distinguishing between the probability distribution of game outcomes implied by bookmaker odds (objective probabilities hereafter) and that implied by betting exchange prices (subjective probabilities henceforth) is crucial in the analysis of stock market efficiency. Tests employing bookmaker odds demonstrate that pre-event stock prices do not reflect expected post-game prices. On the other hand, when investors' beliefs are derived from betting exchange prices, pre-game stock prices are not significantly different from expected post-game prices, computed using investors' subjective (biased) probabilities of game outcomes. This finding supports the notion that the apparent market inefficiency largely follows from investors' inability to assign correct probabilities to game outcomes, and not necessarily from investors' irrational ex-post reactions to wins and losses.

To summarize, the main contribution of this paper is twofold. First, we introduce a novel proxy for investors' beliefs about the likelihood of future event outcomes in order to

[4] While we expect prices of contracts trading on betting exchanges to be a better proxy for investors' beliefs, this proxy has its limitations, which have implications for the interpretation of our results. These limitations are discussed in detail in Section 5.

distinguish between two potential sources of market inefficiency: biased investors' ex-ante expectations or ex-post irrational responses to resolutions of uncertainty. We argue that betting exchange prices are more closely related to investors' subjective expectations than either bookmaker odds or in-sample estimated probabilities of wins, losses, and draws. Second, we show that an important reason for the stock market's apparent inefficient response to soccer game results is the systematic bias in investors' beliefs about the probability distribution of match outcomes. Our evidence is not fully consistent with the hypothesis that irrational reactions (emotions) determine the evolution of stock prices around important matches.

The paper proceeds as follows. In the next section we describe the data and present summary statistics. Section 3 shows that sports performance and operating performance are related and, thus, game results may provide investors with important information about clubs' valuation. We examine the market's response to game outcomes in Section 4. We discuss our proxies for investors' subjective beliefs and objective probabilities of game outcomes, and various biases associated with them in Section 5. Section 6 incorporates investors' pre-game expectations into the tests of post-game returns. We summarize our evidence and conclude in Section 7.

2 Data and summary statistics

Our sample consists of all Champions League and UEFA Cup games (including qualifying rounds) played during the period 1/2000 - 5/2006 and featuring at least one publicly traded club at the time of the match. Overall, there are 20 publicly traded teams from eight countries, ranging from such powerhouses as Manchester United, Juventus and Ajax, to virtually unknown teams such as the British side Millwall and Danish clubs Aalborg and Silkeborg.[5] Our sample teams played in 596 unique matches, 31 of which featured two publicly traded clubs, corresponding to 627 post-game stock returns.

[5]Since we examine only teams that have played at least one game in one of the European competitions during the sample period, our sample includes only a subset of all publicly traded clubs. In addition, not all teams in our sample have been publicly traded throughout the whole sample period. The four Turkish teams went public from 2002 (Beşiktaş) through 2004 (Fenerbahçe) to 2005 (Galatasaray and Trabzonspor), Juventus went public in 2001, and Roma and Borussia Dortmund became public in 2000. The most valuable

We choose to concentrate on international games, rather than national championships or cups, for three reasons. First, we hypothesize and show empirically that games in European competitions are important for clubs' profitability and valuation. Second, UEFA Cup and Champions League are structured as knock-out rounds of pairs of games, for the most part. Hence, a team plays its opponent in a given round twice (home and away), and advances or is eliminated based on the combined outcome of the two games, which are usually scheduled two weeks apart. Because a team's advancement to the next round typically depends solely on its own performance, the team's post-game stock return does not depend (indirectly) on the outcome of games played by other clubs, unlike in the case of national championships. (Such inter-game dependence would contaminate tests of the relation between game results and stock returns.)[6] Third, as discussed in the introduction, we use bookmakers' odds and prices of contracts traded on betting exchanges to assess objective probabilities of game outcomes and investors' subjective beliefs. These data are not available for some of the national leagues and cups for most of our sample period.

We obtain game results along with match dates from the Rec.Sport.Soccer Statistics Foundation at www.rsssf.com. We cross-check the results and dates against those reported by Betexplorer, which is the source of bookmaker odds data (www.betexplorer.com; we discuss the data obtained from this source in detail below). Table 1 presents summary statistics for various game and club characteristics. Panel A reports statistics separately for the 20 teams, Panel B aggregates them by country, and Panel C reports averages for the whole sample.

Insert Table 1 here

The first column in Panel A (B) of Table 6 contains team (country) names in alphabetical order. Successful, established teams tend to play many European matches – over 70 each for Manchester United and Porto, whereas smaller clubs tend to be featured in a handful of games only, as shown in the second column. Large soccer nations – England, Italy, and Portugal – comprise more than 60% of the sample.

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sports franchise in the world, Manchester United, was sold to a private investor and delisted in 2006.

[6] There are some exceptions to the knock-out system. Part of the games in the Champions League are played within four-team group stages, and one of the rounds in the UEFA Cup was structured as a five-team group stage during part of our sample period.

The next two columns report the number of games each team played against other publicly traded opponents and the number of elimination games, defined as either the second game of a knock-out stage or the last game of a group stage. About two thirds of the games in our sample are played in the Champions League competition, as shown in the fifth column. The next column presents the number of games played in advanced stages of the European competitions.[7] About half of the 169 games in advanced stages were played by Manchester United, Juventus, and Porto. The number of home games is presented in the seventh column. Half of the games in our sample are played on public teams' home turf.

The next column contains the number of games in which a team is considered to be the favorite. We characterize as favorite in a given match the team with the higher official UEFA rating prior to the game. Historical ratings are available from www.xs4all.nl/~kassiesa/bert/uefa/data. A club's rating depends on two additive terms: its own performance in European competitions during prior five years, as well as the performance of all teams playing in the club's national league. Thus, if a team has not qualified for a European competition for five consecutive years, its rating equals its country's rating.[8]

The next columns provide the proportions of various game outcomes and the average number of goals scored and received per match. Public teams in our sample won about 42% and lost 33% of their games, tying the remaining ones. This winning record is not overly surprising, given that most of the public teams feature better squads than their typical opponents, at least in the early stages of the competitions. Consequently, teams in our sample advance to subsequent rounds in 55% of the elimination games. Naturally, our sample clubs score on average more goals than their opponents.

The four rightmost columns in Table 1 report soccer clubs' book and market values and

[7] We define quarterfinals, semifinals and finals of the Champions League and the UEFA Cup, as well as the second group stage of the Champions League as advanced stages.

[8] This approach has an advantage over defining favorites/underdogs based on bookmakers' odds (spreads) as in the existing betting literature (e.g., Golec and Tamarkin (1991) and Gray and Gray (1997)). Betting odds depend both on the intrinsic quality of a team and its opponent, and on whether a game is played at home or away. Thus, betting odds tend to be highly correlated with the home/away variable, while our definition of favorites/underdogs is orthogonal to the home/away variable in a large sample.

operating performance measures. Market values and accounting variables are obtained from Datastream. All values are converted into U.S. dollars using contemporaneous exchange rates available from Datastream. For each club, we compute the market value of equity as the product of the number of shares outstanding and the stock price one day prior to the team's game. The table reports the pre-game market capitalization averaged across all games played during the sample period. There is a tremendous variation in soccer clubs' equity values. They range from less than a million dollars for Silkeborg to almost a billion dollars for Manchester United. Similar variation is observed in the clubs' average annual sales and book assets.[9] Finally, the last column in the table reports firms' average annual return-on-assets (ROA), defined as the ratio of EBITDA to lagged book assets. All clubs except for Millwall are profitable on average, with the typical ROA exceeding 15%.

3 Do sports results matter?

The analysis of the market's reaction to game results hinges on the assumption that the latter affect clubs' valuations by influencing their operating performance (e.g., by allowing them to play in additional lucrative games, increasing the compensation from UEFA for participation in its tournaments, raising merchandise sales, advertising revenues, and proceeds from TV rights). Thus, before analyzing stock returns following games, we examine the relation between teams' success in European competitions and their operating performance.

Each year we compute five measures of clubs' sports performance. The first one is the number of games played in the European competitions during the year. Due to the knockout nature of the Champions League and the UEFA Cup, the number of games is highly correlated with performance: more games indicate advancement through more rounds. A similar measure of sports performance is the dummy variable equalling one if the team has reached an advanced stage of one of the two competitions, as defined above, and equalling zero otherwise. Our third measure of performance is a dummy variable equalling one if the firm has played at least one game in the Champions League during the year, with

[9] Accounting variables are not available from Datastream for all four Turkish clubs and for Sporting Lisbon.

the idea that Champions League games are more lucrative and are expected to have a larger positive impact on clubs' fortunes. The fourth measure is the team's UEFA rating. Realizing that ratings may reflect past performance more than expectations of current and future performance, we use annual changes in ratings as our last measure of sports performance.

Armed with these measures of franchises' sports success, we then estimate the following club-year regression:

$$ROA_{i,t} = \alpha + \beta PERF_{i,t} + \varepsilon_{i,t}, \tag{1}$$

where $ROA_{i,t}$ is club i's ratio of EBITDA in year t to book assets in year $t-1$, and $PERF_{i,t}$ is one of the five performance measures above. The regression is estimated using firm fixed effects. Standard errors are clustered by firm, as in Petersen (2008).[10] The results are presented in Table 2.

Insert Table 2 here

The results show that profitability is related to sports performance. The coefficients on all performance measures except for the change in UEFA rating are significantly positive at the 5% level. More importantly the economic impact of a club's successful performance in the European competitions on profitability is large. The coefficient estimates suggest that each game played in the Champions League or the UEFA Cup increases EBITDA by about 0.6 percentage points. Reaching an advanced stage of one of the competitions is associated with a 7.7 percentage points increase in profitability, and participating in the Champions League increases EBITDA by 9.2 percentage points. These effects are by no means trivial relative to the typical ROA of 15.3% reported in Table 1.

The positive relation between a club's sports performance and its operating performance is reassuring. It is also consistent with the analysis of Brown and Hartzell (2001), who find that the operating performance of North-American professional basketball, baseball and football franchises is directly related to the teams' sports performance. Nonetheless, the association between sports and business performance does not necessarily imply that game

[10] The five measures of performance are not used simultaneously due to multicollinearity. Correlations among the performance measures range between 48% and 72%.

results provide information to investors that is important enough to trade on it. To begin our analysis of this question, we compare the trading volume and volatility on days following games to typical off-game trading volume and profitability.

We obtain daily number of shares traded for each club from Datastream and define abnormal trading volume for each of the three days around the game day, $AVOLUME_{i,t}$, as

$$AVOLUME_{i,t} = \ln\left(\frac{VOLUME_{i,t}}{VOLUME_{i,t-5}}\right), \tag{2}$$

where $VOLUME_{i,t}$ is the trading volume on days -1, 0, and 1 relative to the game day and $VOLUME_{i,t-5}$ is the trading volume five trading days before. We normalize the volume on days around games by one-trading-week lagged volume because European games are generally played on weekdays at most once a fortnight and national games are typically played on weekends. Thus, in the vast majority of cases, $t-5$ is an off-game day. Furthermore, comparing $VOLUME_{i,t}$ with $VOLUME_{i,t-5}$ or $VOLUME_{i,t+5}$ eliminates the possible day of the week effect. On rare occasions when two games are scheduled one week apart – this happens sometimes in early qualifying rounds and group stages – we use $VOLUME_{i,t+5}$ or $VOLUME_{i,t-10}$ instead of $VOLUME_{i,t-5}$. Mean abnormal volumes around game days are presented in Panel 1 of Table 3.

Insert Table 3 here

Trading volume of soccer clubs' stocks appears to be abnormally high on game days and on days following games. The mean volume on game days is 20% higher than on off-game days, the difference being statistically significant. The volume on days following games is 30% higher than the off-game-day volume, the difference being highly significant. The finding that trading volume is abnormally high during both game days and days following games supports the notion that important information regarding the likelihood of game outcomes is released not only during games but also prior to games.

Abnormal trading volume is large and significant following wins and losses, but not following draws, consistent with draws being less informative about a team's chances to advance to the next round of the competition. Interestingly abnormal volume is much higher following deciding games than following non-deciding games (55% higher than off-game volume and 19% higher than off-game volume respectively).

Panel B of Table 3 presents mean abnormal volatility around matches, which is defined similar to Duffee (1995), as the absolute value of daily return. Because many daily return observations have a value of zero, especially on off-game days, abnormal volatility is defined as follows:[11]

$$AVOLATILITY_{i,t} = VOLATILITY_{i,t} - VOLATILITY_{i,t-5}. \tag{3}$$

Similar to volume, volatility is abnormally high on days following games – it is 0.68 percentage points higher than that on off-game days. Moreover, abnormal volatility is much higher after losses than after wins (1.28% versus 0.41%), consistent with the asymmetric nature of information contained in wins and losses. These numbers are large. For comparison, the mean off-game volatility is 1.47% and its standard deviation is 2.17%. Similar to trading volume, volatility is much higher after elimination games than after non-deciding ones. Different from the volume results, volatility does not seem to be abnormally high on game days.

These results are consistent with the finding in Brown and Hartzell (2001), who report that the trading volume and volatility of Boston Celtics Partnership shares increases following games. Thus, similar to professional basketball, soccer games provide new information on which investors trade. In the next section we examine the magnitudes of the market's responses to new information contained in game outcomes.

4 Game outcomes and returns

A soccer club's profitability and value is related to its sports performance (see Table 2). Also, investors trade on the information conveyed by its games' outcome (see Table 3). Therefore, we expect soccer clubs' stock prices to react favorably to wins and negatively to losses. In this section we investigate whether this is indeed the case. We use two-day

[11] Defining abnormal volatility as $AVOLATILITY_{i,t} = \ln\left(\frac{VOLATILITY_{i,t}}{VOLATILITY_{i,t-5}}\right)$ for non-zero values of absolute returns provides results very similar to those reported.

windows to measure returns around games: $CR_i = R_{i,0} + R_{i,1}$, where $R_{i,0}$ is the return on club i's stock on game day and $R_{i,1}$ is the return on the following day. The reason for using two-day windows is the volume-based evidence reported above that suggests that important information regarding games and their potential outcomes is released during trading hours of the game day. (Examples include coaches releasing their teams' starting line-ups, providing signals about injuries to players and about expected game strategies).

In addition to examining raw returns, we follow Brown and Hartzell (2001) and compute abnormal returns by estimating the market model for each club each year:

$$R_{i,t \subset T} = \alpha_{i,T} + \beta_{i,T} R_{LM,t} + \varepsilon_{i,t}, \tag{4}$$

where $R_{i,t \subset T}$ is the daily return on stock i on day t belonging to year T, $R_{LM,t}$ is the value-weighted local market index return, and $\varepsilon_{i,t}$ is the daily abnormal return (see Campbell, Lo and MacKinlay (1997)). We estimate the market model on an annual basis because we conjecture and confirm empirically that the intercept in (4) is not constant over time. Many clubs in our sample became public either during the sample period or not long before its start. The literature on the underperformance of recent new issuers (e.g., Loughran and Ritter (1995) and Ritter (1991)), shows that the performance of newly issued stocks in years following their Initial Public Offerings is not stable.[12] Similar to raw returns, we use two-day abnormal returns: $CAR_i = \varepsilon_{i,0} + \varepsilon_{i,1}$ in the empirical tests. Table 4 reports raw and abnormal returns when the sample is partitioned into wins, losses, and draws.[13]

Insert Table 4 here

Panel A presents returns for the whole sample. Consistent with the idea that wins (losses) convey positive (negative) information, wins result in statistically significant average raw (abnormal) returns of 0.7% (0.6%), losses generate highly significant average returns of -2%, whereas returns after draws are not significantly different from zero.

[12] Estimating abnormal returns for the entire sample period as in Brown and Hartzell (2001) provides qualitatively similar results to those reported.

[13] The significance of raw and abnormal returns in Table 4 is assessed using the cross-sectional test (e.g., Boehmer, Musumeci and Poulsen (1991) and Brown and Warner (1985)), in which the t-statistic is computed as the mean return divided by its cross-sectional standard deviation.

In Panel B we further segment the sample to home and away games. Home teams win more frequently than away teams: 173 wins and 64 losses for home teams compared with 93 wins and 145 losses for away teams. Consistent with this finding, the mean return following home wins, 0.4-0.5%, is lower than the one following away wins, 0.9-1%. For the same reason, losses on home turf have a larger impact than losses away from home, -2.8-3% versus -1.6%. Panel C separates pre-game favorites from underdogs. The distinction based on pre-game ratings tends to be borne out on the field: favorites (underdogs) win (lose) approximately twice as many games as they lose (win). Thus, similar to the evidence in Panel B, the market is not overly surprised when favorites win - the mean return of 0.4% is not statistically significant, whereas wins by underdogs convey important positive information - the mean raw return is 1.82%, the mean abnormal return is 1.55%, and both are highly significant. Losses by underdogs are greeted less unfavorably than losses by favorites (mean returns of -1.6-1.7% for underdogs and -2.2% for favorites).

Panel D splits the sample to early and advanced stages of the competitions. Consistent with games at later stages being more uncertain and having larger value consequences, we find that the magnitude of returns after both wins and losses are larger after games in advanced stages than in early ones. Finally, in Panel E we restrict our attention to elimination games and focus on whether a team advances to the next round or is eliminated, rather than on the result of the game per se. Returns following advances to the next round are positive and significant and are higher than returns following wins in Panel A. Returns following eliminations are slightly larger in magnitude than returns following losses. Because the observations in Panels A and E are by no means independent, however, these differences likely underestimate the impact of advances to the next round and eliminations.

Overall, the evidence in Table 4 supports the notion that the outcome of games has an immediate impact on club values. To further examine the effect of game outcomes on stock returns, we complement the univariate analysis by estimating a multivariate regression of post-game returns on indicator variables for wins and losses and their interactions with clubs' and games' observed characteristics:

$$CR_{i,k} = \alpha + \beta_{win} W_{i,k} + \beta_{loss} L_{i,k} + \sum_j \beta_{win\_j} I_{j,i,k} W_{i,k} + \sum_j \beta_{loss\_j} I_{j,i,k} L_{i,k} + \varepsilon_{i,k}, \quad (5)$$

where $W_{i,k}$ equals one if public team k has won game i and zero otherwise, $L_{i,k}$ is the lost game indicator, $I_{j,i,k}$ are three dummy variables, $j = 1, 2, 3$, that equal one if team k played game i at home, if team k was the favorite for the game, and if game i is in an advanced stage of the European competitions respectively. To interpret the intercept of (5) as the mean return following draws, we normalize $I_{j,i,k}$ to have zero means.[14] Table 5 presents the results of estimating (5) using raw returns (columns 1-5) and abnormal returns (columns 6-10).

Insert Table 5 here

Columns 1 and 6 of Table 5 confirm the results in Panel A of Table 4: wins are accompanied by positive, significant returns (relative to returns following the relatively neutral outcomes – draws), and losses result in negative returns that are statistically significant and larger in magnitude than post-win returns. This asymmetry is consistent with the findings of Brown and Hartzell (2001) and Edmans, Garcia and Norli (2007). Furthermore, home losses are associated with a larger negative returns than away losses, which are more likely ex-ante. Wins by favorites, which are also expected, result in significantly lower post-game returns than wins by underdogs, which occur much more rarely. Finally, both wins and losses in advanced stages of the competitions result in returns of larger magnitudes, although only losses in advanced stages have a significantly larger impact in all specifications.

Large stock price changes after losses relative to post-win returns are not sufficient to conclude that the stock market's reaction to game outcomes is inefficient. This finding could be a result of investors' rational ex-ante beliefs. To claim that the market's reaction to game results is inefficient, it is necessary that the mean return around matches is significantly different from zero. Table 6 reports average returns for the whole sample, as well as for various subsamples.

Insert Table 6 here

The mean post-game return is negative across all subsamples, statistically significant at a 5% level in five out of eight cases, and is the largest in magnitude for games played

[14] For example, since half of the games played by public teams' are on home turf, the home indicator variable takes a value of 0.5 for home games and -0.5 for away games.

in advanced stages of the European competitions. This finding is a challenge for market efficiency.

Relying on the behavioral finance literature, we analyze two possible explanations for the inefficient stock price reaction to soccer games' results. First, it is possible that investors "rationally" set prices based on their expectations of post-game club values, yet systematically misestimate the likelihood of various outcomes. If investors tend to be too optimistic about their clubs' chances to succeed, on average, they would be disappointed ex-post, resulting in larger (smaller) negative (positive) surprises than under the premise of efficient capital markets. Thus, the first potential reason for the reported negative post-game returns may be investors' optimism when forming beliefs about the probabilities of potential game outcomes. Another explanation for the apparent market inefficiency is that the reported stock price reaction is driven by investors' post-event emotional reactions, as in the case of national team matches in Edmans, Garcia and Norli (2007). In the next two sections we attempt to disentangle these two potential reasons for the market's inefficient reaction to games' outcome. Specifically, in the next section we examine the extent of investors' optimism and in Section 6 we quantify the effects of this optimism on expected post-game returns.

5 Proxies for investors' beliefs and objective probabilities

To determine whether investors' biased ex-ante beliefs are partially responsible for the negative mean return around soccer games we incorporate measures of investors' expectations in our analysis and compare them with objective probabilities of match outcomes. In what follows, we discuss our proxies for subjective and objective expectations and examine potential biases associated with them.

5.1 Bookmaker odds as a proxy for objective probabilities

Existing studies examining the stock market's reaction to sporting events employ two proxies for the likelihoods of various game outcomes. The first one is bookmaker odds in the case of soccer (e.g., Palomino, Renneboog and Zhang (2005)) and bookmaker spreads in the case of basketball (e.g., Brown and Hartzell (2001)). The second one is in-sample fitted values from models relating game results to ex-ante team characteristics. Edmans, Garcia and Norli (2007) report that the correlation between the two measures is above 90%.

Bookmaker odds are generally found to be unbiased predictors of game outcomes (see Sauer (1998) for a survey of wagering markets literature).[15] Thus, we derive our estimates of objective probabilities of wins, losses, and draws from bookmaker odds. We obtain bookmaker odds from Betexplorer (www.betexplorer.com). This website compiles odds from various bookmakers, reporting the best historical odds for each potential outcome. Betexplorer reports odds for 583 games, corresponding to more than 90% of our sample. We follow Palomino, Renneboog and Zhang (2005) and translate the odds into probabilities using the following transformation

$$prob_{win}^{obj} = \frac{1/O_{win}}{1/O_{win} + 1/O_{draw} + 1/O_{loss}}, \tag{6}$$

where $prob_{win}^{obj}$ is the odds-based probability of a win, and O_{win}, O_{draw}, O_{loss} are the odds of win, tie, and loss, respectively, and similarly for $prob_{draw}^{obj}$ and $prob_{loss}^{obj}$. Panel A of Table 7 shows the comparison between the probabilities based on bookmaker odds and the observed distribution of game outcomes.

The differences between the odds-based probabilities and the in-sample proportions of game outcomes are generally small. For the full sample, on average, bookmakers are almost exactly on target in forecasting winning odds, and they are not far off in predicting the losing odds (32% expected versus 34% realized). When analyzing various subsamples, however, it appears that bookmakers have biased expectations in some cases. For instance, bookmakers predict higher winning probabilities in the advanced stages than the in-sample proportion of wins (38% expected versus 29% realized). In addition, the evidence suggests

[15] There are some exceptions to the efficiency of bookmaker odds/spreads as predictors of match outcomes. For example, Golec and Tamarkin (1991) and Gray and Gray (1991) document that betting on home teams that are underdogs in National Football League matches generates substantial returns net of comissions. Zuber, Gandar and Bowers (1985) also identify profitable strategies associated with football betting. Vlastakis, Dotsis and Markellos (2006) document an "away-favorite" bias in the European soccer bookmaker odds.

a substantial bias when teams are ranked higher than their opponents: on average, bookmakers underestimate (overestimate) the winning (losing) chances of favorites and severely overestimate (underestimate) the winning (losing) chances of underdogs. This finding is in contrast with the evidence in Golec and Tamarkin (1991) and Gray and Gray (1997) of the bias towards favorites in the case of National Football League spreads.

Bookmaker odds, while providing a good measure of the objective probabilities of game outcomes, may not capture investors' subjective ex-ante beliefs (e.g., Levitt (2004)). However, to the extent that investors set post-event prices on the basis of their perceived (i.e. subjective) distribution of post-event prices, pre-event prices reflect traders' beliefs rather than objective probabilities of possible realizations of uncertainty. Unfortunately, investors' subjective expectations are impossible to observe and hard to estimate. In what follows, we propose a new proxy for investors' beliefs and incorporate it in our investigation of the market's inefficient response to soccer game outcomes.

5.2 Betting exchange prices as a proxy for investors' beliefs

Our approach to estimating investors' beliefs relies on prices of contracts traded on betting exchanges or "prediction markets". These trading venues are similar to more traditional exchanges. Prices of traded contracts are determined solely by the demand for and supply of these contracts, with the exchanges' role limited to providing a trading platform and clearing services. An example of such contract is a security paying $1 in case of Manchester United defeating Bayern Munchen in a Champions League game and paying nothing otherwise.[16]

The interpretation of betting exchange prices as beliefs regarding probabilities of game outcomes held by investors in soccer clubs' stocks hinges on four important assumptions.

Assumption 1: Betting exchange equilibrium prices represent traders' beliefs

This assumption is theoretically justified. Wolfers and Zitzewitz (2007) demonstrate that

[16]Some betting exchanges, such as Betfair, quote prices of contracts in the form of odds in order to cater to traders that are more familiar with this way of price quotation.

prediction markets efficiently aggregate traders' beliefs. Specifically, they show that if traders have logarithmic utilities, then equilibrium betting exchange prices equal traders' average beliefs regarding the likelihoods of event outcomes, weighted by traders' wealth. They also show that for other specifications of traders' utilities, prediction market prices are usually close to traders' mean beliefs. Similarly, Gjerstad (2005) shows that for reasonable coefficients of relative risk aversion, equilibrium betting exchange prices are in line with traders' mean beliefs. Thus, abstracting for now from the possibility of arbitrage between betting exchanges and bookmakers, prediction market prices are likely to represent aggregate beliefs of traders.

Assumption 2: The majority of traders in public firms' contracts are public teams' fans

Traders in contracts involving matches of public teams can be split into at least two groups based on which team they support. Thus, betting exchange prices aggregate not only the beliefs of public teams' fans but also the beliefs of opposing teams' fans. To the extent that both groups of traders are overly optimistic regarding their respective teams' winning chances, the equilibrium prices would not equal the mean subjective expectations of public teams' fans. However, if the latter constitute a majority of traders in these contracts, betting exchange prices would reflect over-optimism in public clubs' fans' to some degree.

There are reasons to believe that in a typical match between a public team and a private one the public club's fans are likely to dominate the trading. Casual observation suggests that public teams typically hail from larger cities and have larger stadium capacities, implying a larger fan base. In addition, as demonstrated in Table 1, public teams are typically higher rated than their opponents, a fact also consistent with a larger fan base. To summarize, fans of both public teams and their opponents are likely to be among the traders of respective contracts. Thus, betting exchange prices are not going to equal public teams' fans' beliefs. However, since we expect public teams' fans' to dominate the trading in prediction markets on average, betting exchange prices would provide an estimate of public teams' fans' beliefs that is likely to be biased towards objective probabilities.

Assumption 3: There are limits to arbitrage between betting exchanges and bookmakers
Assuming that traders on betting exchanges monitor odds posted by bookmakers, betting exchange prices are not likely to deviate from prices derived from bookmakers odds by more than the difference between the respective transaction costs. The mean sum of the probabilities of wins, draws, and odds, implied by bookmaker odds, is about 1.08, resulting in the mean transaction cost of 8%, while the average fee charged by the betting exchanges in our sample is close to 3%. Thus, a difference of up to 5% between betting exchange prices and bookmakers odds can not be arbitraged away and can persist. In addition, trading on betting exchanges may have intangible benefits. For example, betting exchanges, unlike bookmakers, allow trading during games. In addition, betting exchanges may serve as social networks for teams' fans. While these considerations may result in a larger upper bound for the difference between betting exchange prices and bookmaker odds, large deviations of traders' beliefs from bookmaker odds are not going to be fully reflected in equilibrium betting exchange prices.

Assumption 4: Betting exchanges and stock markets are integrated While there is no guarantee that traders on betting exchanges hold soccer clubs' shares, there are reasons to believe that they do. Numerous studies document investors' tendency to invest in stocks they are familiar with. Examples include home country bias (French and Poterba (1991)), local bias of individual investors (Huberman (2001)) and mutual fund managers (Coval and Moskowitz (1999)), employees' tendency to hold disproportionately large positions in their employer's stock (Benartzi (2001)). Soccer fans trading on betting exchanges are clearly familiar with their clubs. Thus, we argue that they are likely to hold their teams' shares and betting exchanges are at least to some degree integrated with markets on which clubs' stocks trade.

Because the assumptions above are not likely to be fully satisfied in the data, the validity of our proposed measure of investors' beliefs is ultimately an empirical issue. As we show below, our approach leads to results that are quite different from those obtained using the traditional bookmaker odds-based proxy for the probability distribution of possible game outcomes.

We obtain the prices of contracts on wins, losses, and draws of our sample teams from two betting exchanges: Betfair (www.betfair.com) and Tradesports (www.tradesports.com). Betfair is by far the largest betting exchange in the world. The typical volume of contracts traded on this exchange is quite large, over \$240,000 for each contract (over \$320,000 for win- and loss-contracts and about \$55,000 for draw-contracts). The volume on Tradesports is several orders of magnitudes smaller. Thus, we use Betfair as our main source to estimate subjective probabilities of game outcomes. The main drawback is that Betfair historical data only start in 2004, limiting the number of contracts on the outcome of games to 537, corresponding to 179 sample games. Thus, we complement these data using Tradesports contracts for years 2001-2003. Tradesports data are spotty, however. In addition, Tradesports contracts generally feature larger, more established clubs, which are more likely to violate our second assumption, regarding relative fan bases of public teams and their opponents. After imposing the restriction of at least \$100 volume on each of the three possible contracts on a given game, we obtain data for contracts on 48 more games, increasing our betting exchange prices sample to 227 games.[17]

To calculate investors' subjective probabilities of each of the three possible outcomes, we compute the volume-weighted average of prices on each contract matched prior to the start of the game (contracts that are not "in play"). Because the sum of the average prices on win, draw, and loss contracts does not usually equal exactly one, we scale each contract's price by the combined price on the three contracts. For example, the implied probability of a win, $prob_{win}^{subj}$, is computed as

$$prob_{win}^{subj} = \frac{P_{win}}{P_{win} + P_{draw} + P_{loss}}, \tag{7}$$

where P_{win}, P_{draw}, and P_{loss} are the prices of win, draw, and loss contracts respectively. Panel B of Table 7 reports the typical probabilities implied by betting exchange prices for various contracts and compares them to the in-sample distribution of match outcomes.

Insert Table 7 here

On average, investors trading on betting exchanges are overly optimistic about our sample teams' prospects. They assign an average probability of 43% (31%) to a win (loss), while

[17]Limiting our sample to Betfair prices only does not alter the qualitative results reported below.

the in-sample proportion of wins (losses) is 38% (37%). The differences between expected and realized outcomes are marginally significant. Nonetheless, except for the case of teams playing on home turf, the difference between expected and in-sample probabilities of wins (losses) are uniformly positive (negative) and are statistically significant in many cases. Investors' optimism is most pronounced for games in advanced stages of the competitions: the win probability of 35% implied by exchange prices is significantly different from the realized proportion of wins of 18%. Furthermore, investors are grossly overoptimistic about the winning chances of underdogs (27% expected versus 18% realized) and of teams playing away from home (32% expected versus 21% realized).

One potential reason for the differences between investors' beliefs and game results may be that our subsample of games with available data on betting exchange prices comprises a set of particularly surprising game outcomes that could not have been rationally expected ex-ante. To investigate this possibility, in Panel C of Table 7 we compare betting exchange prices with probabilities implied by bookmaker odds for the subset of 217 games for which both are available. Traders on betting exchanges are significantly more optimistic than bookmakers across all subsamples. The average betting exchange-based probability of winning is 43%, compared with the average odds-based probability of 39%. Betting exchange investors are especially optimistic in early stages of the competitions and when teams are favorites or play at home. In these cases, the probabilities of winning (losing) implied by betting exchange prices are 5-6% higher (lower) than those implied by bookmaker odds.

To complement the univariate analysis above, we estimate ordered logit models relating games' outcome to betting exchange prices and game characteristics. This method represents an extension of the test proposed in Gray and Gray (1997) for the case of football spreads. Specifically, we estimate the following model:

$$\ln\left(\frac{prob(Y_i \leq result)}{1 - prob(Y_i \leq result)}\right) = \alpha_{result} - \beta_{prob_{win}} prob_{win} - \beta_{prob_{draw}} prob_{draw} - \sum_j \beta_j I_{j,i}, \quad (8)$$

where $Y_i = 1$ for wins, $Y_i = 2$ for draws, and $Y_i = 3$ for losses. $result$ can take the values of 1 or 2. $prob_{win}$ and $prob_{draw}$ take the values of $prob^{subj}_{win}$ and $prob^{subj}_{draw}$, in the case of betting exchange-based probabilities, or the values of $prob^{obj}_{win}$ and $prob^{obj}_{draw}$, in the case of bookmaker odds-based probabilities. $I_{j,i}$ are de-meaned dummy variables for home/away game, favorite/underdog status, and stage of a competition, similar to (5).[18] Table 8 presents the estimates of (8). The coefficient estimates on the indicator variables, $I_{j,i}$, are of main interest. Under the null hypothesis of no bias, $I_{j,i}$ should have no explanatory power; significant coefficient estimates would suggest specific biases in the predicted probabilities of possible game outcomes. Columns 1 through 5 examine biases in the exchange-based probabilities, while the remaining columns (6-10) present the results for the bookmaker odds-based probabilities.

Insert Table 8 here

Not surprisingly, both $prob_{win}^{subj}$ and $prob_{win}^{obj}$ are very good predictors of whether a sample team wins, as evidenced by the near-zero p-values of the corresponding coefficients' χ^2. Consistent with the univariate results in Table 7, the coefficient estimates for home games suggest a "home bias", when using the exchange-based probabilities. The regressions using bookmaker-odds-based probabilities reveals no statistically significant bias. These results, together with the differences between the probabilities implied by bookmaker odds and by betting exchange prices reported in the previous table, underscore the importance of choosing a valid proxy for investors' expectations when examining the sources of market inefficiency.

6 Returns adjusted for expected outcomes

The evidence above demonstrates that the ex-ante probabilities of game outcomes implied by prices of contracts traded on betting exchanges are biased, on average, both relative to the actual distribution of game outcomes and relative to the probabilities of outcomes implied by bookmaker odds. In this section we investigate whether investors' biased beliefs alone can explain the negative mean return following soccer games.

If investors set a club's stock price prior to a game, V_{before}, as the weighted average of the post-game values, with weights equal to their subjective probabilities of game outcomes,

[18] If a game features two public teams we randomly choose one team for which the probabilities of outcomes are estimated. This explains the slightly lower number of observations than the number of available post-game returns.

then V_{before} can be expressed as

$$V_{before} = prob_{win}^{subj} V_{win} + prob_{draw}^{subj} V_{draw} + (1 - prob_{win}^{subj} - prob_{draw}^{subj}) V_{loss}, \tag{9}$$

where V_{win}, V_{draw}, and V_{loss} are the club's post-game rational values conditional on game outcome. Then, the post-game realized return, R, is

$$\begin{aligned} R = \frac{V_{win}W + V_{draw}D + V_{loss}L - V_{before}}{V_{before}} + \varepsilon = \\ \frac{(V_{win} - V_{loss})}{V_{before}} W + \frac{(V_{draw} - V_{loss})}{V_{before}} D - \\ \frac{(V_{win} - V_{loss})}{V_{before}} prob_{win} - \frac{(V_{draw} - V_{loss})}{V_{before}} prob_{draw} + \varepsilon, \end{aligned} \tag{10}$$

where W, D, and L are indicator variables for wins, draws, and losses, respectively, and ε is a zero-mean error term. (10) provides the means to test whether pre-game prices are determined solely based on investors' (possibly biased) beliefs about game outcomes and on post-game club values conditional on game outcomes. Under this null hypothesis, the coefficients in the following regression

$$R_i = \alpha + \beta_W W_i + \beta_{prob_{win}} prob_{win,i} + \beta_D D_i + \beta_{prob_{draw}} prob_{draw,i} + \varepsilon_i, \tag{11}$$

must satisfy the set of restrictions:

$$\beta_W = -\beta_{prob_{win}}, \ \beta_D = -\beta_{prob_{draw}}, \ \alpha = 0. \tag{12}$$

In Table 9, we provide estimates of model (11) and test the set of restrictions in (12).

Insert Table 9 here

The estimates of the unrestricted model in (11) can be interpreted as follows. The intercept is the mean return after a loss when the team is expected to lose with certainty ($W = 0$, $D = 0$, $prob_{win,i} = 0$, $prob_{draw,i} = 0$). $\alpha + \beta_{I_{win}}$ reflects the mean return after a win when investors were expecting a loss, $\alpha + \beta_{I_{win}} + \beta_{prob_{win}}$ is the return after an expected win, and $\alpha + \beta_{prob_{win}}$ corresponds to the mean return after a loss when investors were expecting a win.

In columns 1-4 of Table 9, we estimate model (11) using betting exchange-based probabilities. The evidence reported in the first two columns, where no restrictions are imposed, is consistent with the hypothesis that biases in investors' ex-ante beliefs alone can explain the market's inefficient response to game outcomes. The intercepts in both regressions, using raw returns or abnormal returns, are not significantly different from zero, suggesting that the market does not react to expected losses. The estimates of β_W and $\beta_{prob_{win}}$ are roughly equal in magnitude, and have positive and negative signs, respectively, implying that expected wins do not result in a significant market reaction. The Wald test reported at the bottom of the table fails to reject the set of restrictions in (12), regardless of the return measure used. The estimates of the model incorporating the set of restrictions in (12),

$$R_i = \beta_{win}(W - prob_{win,i}) + \beta_{draw}(D - prob_{draw,i}) + \varepsilon_i, \tag{13}$$

show that when the probability of a win increases by one percentage point and that of a loss decreases by the same amount, the post-game mean return decreases by 2.4-2.6 basis points. As shown below, the effect of pre-game expectations on post-game investors' reaction plays an important role in explaining the negative mean returns following Champions League and UEFA Cup games.

The inability to reject the restrictions in (12) stands in contrast to the evidence reported in Edmans, Garcia and Norli (2007), who show that controlling for ex-ante expectations cannot explain the market's inefficient response to international soccer game results. An important reason for this discrepancy is that we use probabilities derived from betting exchange prices as a proxy for investors' beliefs. These estimates of subjective probabilities differ systematically from the in-sample distribution of game outcomes. Edmans, Garcia and Norli, on the other hand, use in-sample fitted values of match results conditional on team characteristics, which results in estimates of win and loss probabilities that are unbiased on average, while estimating a regression similar to (11).

To confirm our conjecture that differences in the measure of investors' expectations may explain the discrepancy between our results and those in Edmans, Garcia and Norli (2007), in columns 5-8 of Table 9, we estimate models (11) and (13) using the probabilities implied by bookmaker odds. As shown in Table 7, on average, bookmakers' implied probabilities are not significantly different from the realized distribution of game outcomes. Based on the Wald test reported at the bottom of columns 5 and 6, the set of restrictions in (12) can be comfortably rejected at a 5% confidence level – with p-values of 0.025 at most. Therefore, using investors' subjective expectations, as proxied by betting exchange prices, generate results that are very different from those obtained using objective expectations, as proxied by bookmaker odds.

Another way to test whether the differences in investors' beliefs and objective probabilities of game outcomes are sufficient to explain the negative mean returns following games is to compute the returns one would expect given the documented biases in investors' beliefs. If a club's pre-game price is set based on investors' (subjective) expected post-game club value, then the pre-game price is given by (9). The expected post-game value under the true probability distribution, $E(V_{after})$, is

$$E(V_{after}) = prob_{win}^{obj} V_{win} + prob_{draw}^{obj} V_{draw} + (1 - prob_{win}^{obj} - prob_{draw}^{obj}) V_{loss}, \qquad (14)$$

where $prob_{win}^{obj}$ and $prob_{draw}^{obj}$ denote the true likelihoods of winning and tying respectively. Then the expected post game return is

$$E(R) = \frac{E(V_{after}) - V_{before}}{V_{before}} = \\ (prob_{win}^{obj} - prob_{win}^{subj}) \frac{V_{win} - V_{loss}}{V_{before}} + (prob_{draw}^{obj} - prob_{draw}^{subj}) \frac{V_{draw} - V_{loss}}{V_{before}}. \qquad (15)$$

It follows from (10) that measures of $\frac{V_{win} - V_{loss}}{V_{before}}$ and $\frac{V_{draw} - V_{loss}}{V_{before}}$ are given by the estimated coefficients of the restricted model in (13), $\widehat{\beta_{win}}$ and $\widehat{\beta_{draw}}$ respectively. Multiplying these estimates by the difference between the in-sample proportions of wins and draws and investors' subjective estimates of the probabilities of wins and draws, provides an estimate of the mean expected post-game return that accounts investors' overly optimistic ex-ante beliefs. Table 10 reports the results of this analysis for the whole sample (Panel A) and for various subsamples of games (Panels B through D).

Insert Table 10 here

The biases in investors' estimated probabilities of game outcomes lead to expected negative mean return of about -0.15% for the whole sample, and larger negative returns for away games, games played by underdogs, and games played in advanced stages of the competitions. This is consistent with the biases in investors' beliefs documented in Table

7: investors have especially optimistic beliefs regarding games in advanced stages, games played away from home, and games of underdogs.

The two rightmost columns in Table 10 report mean "adjusted returns" for the full sample and for various subsamples. Following Mitchell and Stafford (2000), the adjusted returns are computed by subtracting expected returns, as defined above, from realized average returns reported in Table 6. Biases in investors' beliefs are responsible for about a third of the magnitude of the mean realized post-game returns. More importantly, after adjusting for biased ex-ante beliefs, the "surprise" component of unconditional mean return is no longer significant (at a 5% level) within the full sample. This is also true for most subsamples. The mean adjusted raw return is significant only for games in advanced stages and for home games, whereas the mean adjusted abnormal return is only significant for the sample of home games. Importantly, since, as argued in Section 5, our proxy for investors' beliefs is likely biased towards objective probabilities of game outcomes, our results may underestimate the magnitude of the effect of investors' optimism and overstate the effect of (irrational) emotional post-game reactions.

The evidence in this section supports the idea that investors' inability to correctly anticipate game outcomes is largely responsible for the significantly negative mean abnormal return following European soccer matches. However, while our findings show that investors' biased ex-ante beliefs are an important component of the market's post-game reaction, they do not rule out the possibility of emotional ex-post reactions affecting post-game returns as well. Our tests are based on isolating the portion of post-game returns that are due to investors' overly optimistic expectations of game outcomes. Such tests are not structured in a way that enable us to formally reject the hypothesis that post-game emotional reactions are responsible for mean negative return around games. In other words, our tests have the power to reject the null hypothesis stating that post-game returns are not affected by investors' irrational post-game reactions. However, they do not have the power to reject the alternative hypothesis that returns are driven in part by ex-post emotional reactions. Hence, more powerful tests are needed in order to be able to provide conclusive evidence regarding the irrational post-game reaction hypothesis.

7 Conclusions

We investigate the effects of the two components of investor sentiment – biased ex-ante estimates of probabilities of future event outcomes and emotional reactions to these outcomes – on stock returns of publicly traded European soccer clubs around important matches. Consistent with past studies of stock market reaction to sports results (e.g., Brown and Hartzell (2001) and Edmans, Garcia and Norli (2007)), we find that the market's reaction to soccer game results is asymmetric. Losses result in significantly negative returns that are much larger in magnitude than positive returns following wins. Overall, the mean return following games is significantly negative. This finding indicates that the market does not react efficiently to the outcome of soccer games played by publicly traded clubs.

Distinguishing between the two types of investor sentiment that drives this inefficiency can be crucial for firm value maximization in settings extending far beyond public sports franchises. Firms' investment decisions, which include both capital investments and acquisitions of other firms, as well as corporate control decisions, are based in part on firms' observed market values. Thus, knowing whether market values are more efficient prior to resolutions of uncertainty or after uncertainties are resolved can facilitate decision making and enhance firm values.

We introduce a new proxy for investors' beliefs that is based on prices of contracts traded on betting exchanges and argue that this proxy is more closely related to investors' subjective expectations than proxies based on bookmaker odds or in-sample predicted likelihoods of game outcomes. The evidence based on our novel measure suggests that the observed market inefficiency is caused, in substantial part, by investors' inability to form unbiased beliefs about future event outcomes. Investors in soccer clubs tend to be overly optimistic about their teams' prospects, leading, more often than not, to disappointments upon resolution of the uncertainty characterizing sporting events. It must be noted, however, that while our results are not entirely consistent with ex-post emotional reactions driving post-game returns, our analysis does not have the power to reject the post-game irrational reaction hypothesis.

While we cannot generalize our conclusions on the nature of investor sentiment beyond the special case of sport sentiment examined here, our approach to analyzing deviations from market efficiency can potentially be applied to other settings. An analysis of the causes of investor sentiment in additional settings depends crucially on the ability to estimate investors' beliefs regarding the likelihood of future events. Developing prediction markets featuring contracts based on economic and financial uncertainties, as suggested by Arrow et al. (2007), may provide a way to estimate investors' subjective expectations of future events. Analyzing potential biases in the prices of event contracts could enhance our understanding of the observed deviations from capital market efficiency and allow firms to make value-maximizing decisions.

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Table 1 – Match statistics, market values, and operating performance measures of publicly traded soccer clubs

This table reports match statistics, market values, and operating performance measures of 20 soccer clubs that were publicly traded at any time between January, 2000 and June, 2006 and have played at least one game in the Champions League or UEFA Cup during this period. All Champions League and UEFA Cup games listed by Rec.Sport.Soccer Statistics Foundations at www.rsssf.com are included in the sample. *Panel A* reports summary statistics by club, *Panel B* reports country-level statistics, and *Panel C* reports statistics for the whole sample. *# games* is the number of matches played. *# games public opponents* is the number of matches played against another publicly traded club. *# games elimination* is the number of matches that are either the second game of a knock-out stage or the last game of a group stage. *# games Champions League* is the number of matches played in the Champions League competition. *# games advanced stages* is the number of matches played in quarterfinal, semifinal, and final stages of the Champions League and the UEFA Cup, as well as the second group stage of the Champions League. *# games home* is the number of matches played at home. *# games favorite* is the number of matches in which the team's UEFA rating prior to the match is higher than its opponent's one. The ratings are obtained from www.xs4all.nl/~kassiesa/bert/uefa/data. *Win* is the proportion of matches won. *Loss* is the proportion of matches lost. *Advance* is the proportion of elimination matches after which a team moved on to the next stage of the competition. *Goals Own:Opp* is the mean number of own versus opponent goals. Market values and accounting variables are from Datastream, they are expressed in U.S. dollars based on exchange rates from Datastream. *MV equity* is the average market value of equity over the sample period, computed as the average of the product of the number of shares outstanding and the stock price one day prior to the games. *Sales* (*Assets*) is the average annual sales (book assets) over the sample period. *ROA* is the average annual return on assets, defined as the ratio of EBITDA to lagged book assets.

	Match statistics											Market values and performance measures			
	# games	# games public opponents	# games elimination	# games Champions League	# games advanced stages	# games home	# games favorites	Win	Loss	Advance	Goals Own:Opp	Market value equity ($MM)	Sales ($MM)	Assets ($MM)	ROA
Panel A - By Team															
Aalborg (DEN)	6	0	3	0	0	3	2	0.17	0.50	0.33	0.7:1.5	9.1	12.6	22.9	0.091
Ajax (NED)	50	0	13	44	10	25	26	0.34	0.34	0.46	1.4:1.1	130.9	63.7	116.9	0.175
Aston Villa (ENG)	2	0	1	0	0	1	2	0.50	0.50	0.00	1.5:1.5	26.6	52.7	101.9	0.096
Besiktas (TUR)	32	0	11	6	2	15	16	0.34	0.41	0.64	1.5:1.3	111.6			
Borussia Dortmund (GER)	35	0	10	27	11	16	28	0.46	0.31	0.58	1.5:1.2	89.0	95.3	219.9	0.164
Brondby (DEN)	21	2	10	9	0	10	14	0.33	0.43	0.40	1.3:1.3	34.2	16.3	59.1	0.109
Celtic (SCO)	52	2	19	26	7	27	26	0.48	0.37	0.63	1.7:1.2	35.6	83.4	126.2	0.080
Fenerbahce (TUR)	13	0	3	11	0	6	0	0.23	0.69	0.00	1.4:2.4	250.9			
Galatasaray (TUR)	22	0	6	18	4	11	15	0.23	0.46	0.17	1:1.3	78.3			
Juventus (ITA)	51	4	15	51	25	25	35	0.51	0.31	0.67	1.6:1.1	254.7	202.4	464.5	0.196
Lazio (ITA)	52	4	14	34	16	26	50	0.42	0.33	0.63	1.6:1.3	175.1	98.3	440.3	0.077
Manchester United (ENG)	81	4	19	81	36	41	76	0.54	0.21	0.57	1.9:1	897.3	222.8	368.0	0.234
Millwall (ENG)	2	0	1	0	0	1	2	0.00	0.50	0.00	1:2	15.6	11.7	32.8	-0.183
Newcastle (ENG)	35	2	13	14	12	18	21	0.60	0.26	0.69	1.9:1.3	79.4	137.1	291.5	0.129
Porto (POR)	75	7	25	52	29	37	53	0.39	0.32	0.67	1.5:1.1	41.5	28.4	97.4	0.104
Roma (ITA)	56	3	16	30	12	28	38	0.39	0.29	0.53	1.4:1.1	129.5	113.4	322.4	0.206
Silkeborg (DEN)	2	0	1	0	0	1	0	0.00	1.00	0.00	0.5:2.5	0.9	5.1	7.7	0.111
Southampton (ENG)	2	0	1	0	0	1	2	0.00	0.50	0.00	0.5:1	19.1	64.1	102.6	0.211
Sporting (POR)	36	3	13	9	5	20	22	0.42	0.36	0.53	1.7:1.5	42.1			
Trabzonspor (TUR)	2	0	1	2	0	1	2	0.50	0.50	0.00	1:1.5	90.4			

	Match statistics											Market values and performance measures			
	# games	# games public opponents	# games elimination	# games Champions League	# games advanced stages	# games home	# games favorites	Win	Loss	Advance	Goals Own:Opp	Market value equity ($MM)	Sales ($MM)	Assets ($MM)	ROA
Panel B - By Federation															
DENMARK	29	2	14	9	0	14	16	0.28	0.48	0.36	1.1:1.4	26.7	14.9	49.9	0.106
ENGLAND	122	6	35	95	48	62	103	0.54	0.24	0.57	1.8:1.1	619.5	189.4	331.9	0.194
GERMANY	35	0	10	27	11	16	28	0.46	0.31	0.58	1.5:1.2	89.0	95.3	219.9	0.164
ITALY	159	11	45	115	53	79	123	0.44	0.31	0.60	1.5:1.2	184.6	137.0	406.5	0.161
NETHERLAND	50	0	13	44	10	25	26	0.34	0.34	0.46	1.4:1.1	130.9	63.7	116.9	0.175
PORTUGAL	111	10	38	61	34	57	75	0.40	0.33	0.62	1.5:1.2	41.7	28.4	97.4	0.104
SCOTLAND	52	2	19	26	7	27	26	0.48	0.37	0.63	1.7:1.2	35.6	83.4	126.2	0.080
TURKEY	69	0	21	37	6	33	33	0.29	0.48	0.38	1.3:1.5	126.6			
Panel C - Whole Sample	627	31	195	414	169	313	430	0.42	0.33	0.55	1.6:1.2	208.3	114.4	261.9	0.153

Table 2 – Clubs' operating income and sports performance

This table presents panel regression estimates of the relation between the *Return n Assets (ROA)* of publicly traded soccer clubs and their performance in Champions League and UEFA Cup competitions. *Market Value* is the market value of equity of a sample club at the end of year *t*. *ROA* is a club's ratio of EBITDA in year t to book assets in year $t - 1$. *Champions League dummy* equals one if the club played at least one game in the Champions League competition during year *t*. *High stage dummy* equals one if the team reached an advanced stage of either of the two European competitions during year *t*, as defined in Table 1. *# games* is the number of games played in the two European competitions during year *t*. UEFA Rating is the team's year-*t* rating obtained from www.xs4all.nl/~kassiesa/bert/uefa/data. Change in rating is the difference between year-*t* rating and year-*t-1* rating. All models include club-level fixed effects. Standard errors of coefficient estimates are clustered by firm, as in Petersen (2007), and the corresponding t-statistics are reported in parentheses.

	Return on Assets$_t$				
	[1]	[2]	[3]	[4]	[5]
Intercept	0.083	0.097	0.091	0.058	0.115
	(3.55)	(4.07)	(3.89)	(2.14)	(4.48)
CHAMPIONS DUMMY$_t$	0.092				
	(2.94)				
HIGH STAGE DUMMY$_t$		0.077			
		(2.39)			
NUMBER OF GAMES$_t$			0.006		
			(2.15)		
UEFA Rating$_t$				0.001	
				(3.18)	
Change in UEFA Rating$_t$					0.002
					(1.64)
N	93	93	93	93	93
R squared	0.582	0.551	0.543	0.592	0.526

Table 3 – Trading volume and volatility around game days

Panel 1 presents mean abnormal daily trading volume around Champions League and UEFA Cup game days. We obtain the number of shares traded daily for each club from Datastream and define abnormal trading volume for three days around a game, $AVOLUME_{i,t}$, as:

$$AVOLUME_{i,t} = ln(VOLUME_{i,t}/VOLUME_{i,t-5})$$

where $VOLUME_{i,t}$ is the trading volume on days -1, 0, and 1 relative to game days and $VOLUME_{i,t-5}$ is the trading volume five trading days before.

Panel 2 presents abnormal return volatility around game days. Volatility is defined as the absolute value of daily return. Abnormal volatility is

$$AVOLATILITY_{i,t} = VOLATILITY_{i,t} - VOLATILITY_{i,t-5}$$

where $VOLATILITY_{i,t}$ is the absolute return on days -1, 0, and 1 relative to game days and $VOLATILITY_{i,t-5}$ is the absolute return five trading days before.

On rare occasions when a club plays two games one week apart – this happens sometimes in qualifying rounds, we use $VOL_{i,t+5}$ instead. The column *All Games* reports the mean abnormal volume using all days following Champions League and UEFA Cup games. The column *Wins* (*Draws*, *Losses*) reports mean abnormal volume for days following a Champions League and UEFA Cup game won (tied, lost) by a sample club. In parentheses, the table reports t-statistics for H_0: $mean(AVOL)=0$. *N* is the number of club-games in each subsample with available data on trading volume.

Panel A - Abnormal trading volume

Full sample	Day	All Games	Wins	Draws	Losses
	-1	8.33%	3.33%	10.37%	13.24%
		(1.70)	(0.39)	(1.06)	(1.92)
	0	20.41%	22.02%	12.65%	23.95%
		(3.95)	(2.68)	(1.33)	(2.63)
	1	30.36%	36.24%	7.40%	39.39%
		(5.45)	(4.34)	(0.73)	(3.75)
	N	582	248	140	194

Non-deciding games	Day	All Games
	0	14.38%
		(2.29)
	1	19.13%
		(3.00)
	N	402

Deciding games	Day	All Games	Advances	Eliminations
	0	33.87%	32.67%	35.20%
		(3.76)	(2.50)	(2.85)
	1	55.41%	47.86%	63.86%
		(5.10)	(3.02)	(4.34)
	N	180	95	85

Panel B - Abnormal volatility

Full sample	Day	All Games	Wins	Draws	Losses
	-1	0.16%	0.23%	0.27%	-0.01%
		(1.54)	(1.44)	(1.49)	(-0.08)
	0	0.11%	-0.11%	0.39%	0.18%
		(0.91)	(-0.61)	(1.68)	(0.96)
	1	0.68%	0.41%	0.29%	1.28%
		(5.61)	(2.63)	(1.25)	(5.32)
	N	582	248	140	194
Non-deciding games	**Day**	**All Games**			
	0	0.04%			
		(0.31)			
	1	0.47%			
		(3.54)			
	N	402			
Deciding games	**Day**	**All Games**	**Advances**	**Eliminations**	
	0	0.24%	0.36%	0.10%	
		(1.29)	(1.37)	(0.39)	
	1	1.12%	0.39%	1.94%	
		(4.56)	(1.45)	(4.74)	
	N	180	95	85	

Table 4 – Post-match returns by game outcome

This table presents mean two-day raw and abnormal returns around games won, lost, or tied by publicly traded soccer clubs participating in Champions League and UEFA Cup competitions. Club *i*'s *Raw return* equals ($R_{i,0}+R_{i,1}$), where $R_{i,0}$ is club *i*'s stock return on game day and $R_{i,1}$ is the return on the following day. The market model for each club *i* in each calendar year, *T*, is estimated as

$$R_{i,t\subset T} = \alpha_{i,T} + \beta_{i,T} R_{LM,t} + \varepsilon_{i,t},$$

where $R_{i,t}$ is the daily return on stock *i* on day *t* belonging to year *T*, $R_{LM,t}$ is the value-weighted local market return, and $\varepsilon_{i,t}$ is the daily abnormal return. Club *i*'s *Abnormal return* equals ($\varepsilon_{i,0}+\varepsilon_{i,1}$). The columns under *Wins* (*Draws*, *Losses*) correspond to Champions League and UEFA Cup games won (tied, lost) by a sample club. *Panel A* presents returns after wins, losses, and draws for the whole sample. *Panel B* separates the sample into home and away games. *Panel C* separates the sample into pre-game favorites and underdogs. *Panel D* segments the sample into early and advanced stage games. *Panel E* is restricted to elimination games. In parentheses, the table reports t-statistics for H_0*: mean(Return)=0*. *N* is the number of club-games in each subsample.

	Win			Draw			Loss		
	Raw return	Abnormal return	N	Raw return	Abnormal return	N	Raw return	Abnormal return	N
Panel A - All games	0.68%	0.57%	266	-0.26%	-0.13%	152	-2.00%	-1.95%	209
	(3.17)	(2.63)		(-0.76)	(-0.41)		(-7.52)	(-7.47)	
Panel B - Home and away									
Home games	0.52%	0.41%	173	-0.58%	-0.44%	76	-3.01%	-2.78%	64
	(2.02)	(1.57)		(-1.53)	(-1.21)		(-4.97)	(-4.77)	
Away games	0.98%	0.88%	93	0.07%	0.18%	76	-1.56%	-1.59%	145
	(2.56)	(2.25)		(0.12)	(0.33)		(-5.79)	(-5.85)	
Panel C - Favorites and underdogs									
Favorites	0.43%	0.36%	219	-0.14%	-0.02%	100	-2.25%	-2.24%	111
	(1.84)	(1.50)		(-0.33)	(-0.06)		(-6.76)	(-6.62)	
Underdogs	1.82%	1.55%	47	-0.48%	-0.34%	52	-1.72%	-1.62%	98
	(3.75)	(3.32)		(-0.87)	(-0.66)		(-4.05)	(-4.02)	
Panel D - Advanced and early stages									
Early stages	0.54%	0.38%	212	0.12%	0.23%	98	-1.60%	-1.53%	148
	(2.39)	(1.66)		(0.28)	(0.56)		(-5.11)	(-5.03)	
Advanced stages	1.22%	1.34%	54	-0.94%	-0.79%	54	-2.98%	-2.96%	61
	(2.16)	(2.31)		(-1.76)	(-1.56)		(-6.11)	(-6.14)	
Panel E - Advances and eliminations	Advances						Eliminations		
	Raw return	Abnormal return	N				Raw return	Abnormal return	N
	1.10%	0.97%	103				-2.18%	-2.22%	92
	(2.43)	(2.23)					(-4.86)	(-4.82)	

Table 5 – Multivariate analysis of the relation between returns and sports performance

This table presents OLS estimates of the relation between post-game returns, game outcomes, and other match characteristics. In particular, the following model is estimated:

$$Return_i = \alpha_i + \beta_{Win} W_i + \beta_{Loss} L_i + \sum_j \beta_{Win\_j} I_{j,i} W_i + \sum_j \beta_{Loss\_j} I_{j,i} L_i + \varepsilon_i$$

where $Return_i$ is club-game i's raw or abnormal return as defined in Table 4; W_i (L_i) is an indicator variable that equals one if the publicly traded team won (lost) the game, and equals zero otherwise; $I_{j,i}$s are three indicator variables that equal one if the team played at home (*Home*), if it was the favorite for the game (*Favorite*), and if the game was played in an advanced stage of the competition (*Advanced stage*), respectively. All indicator variables ($I_{j,i}$) are normalized to have zero mean. In parentheses, the table reports t-statistics for H_0: *coefficient=0*.

	Raw Returns					Abnormal Returns				
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Intercept	-0.26%	-0.26%	-0.26%	-0.26%	-0.26%	-0.13%	-0.13%	-0.13%	-0.13%	-0.13%
	(-0.84)	(-0.84)	(-0.84)	(-0.84)	(-0.85)	(-0.44)	(-0.44)	(-0.44)	(-0.44)	(-0.44)
Win	0.94%	1.00%	1.13%	0.98%	1.23%	0.71%	0.78%	0.87%	0.77%	0.99%
	(2.43)	(2.57)	(2.87)	(2.54)	(3.09)	(1.86)	(2.02)	(2.25)	(2.03)	(2.52)
Loss	-1.75%	-2.03%	-1.83%	-1.72%	-2.15%	-1.82%	-2.05%	-1.91%	-1.79%	-2.18%
	(-4.33)	(-4.86)	(-4.46)	(-4.27)	(-5.06)	(-4.56)	(-4.98)	(-4.73)	(-4.51)	(-5.20)
Win * Home		-0.46%			-0.49%		-0.47%			-0.49%
		(-0.95)			(-1.02)		(-0.98)			(-1.04)
Loss * Home		-1.44%			-1.56%		-1.19%			-1.31%
		(-2.55)			(-2.73)		(-2.13)			(-2.34)
Win * Favorite			-1.39%		-1.34%			-1.19%		-1.09%
			(-2.29)		(-2.20)			(-1.99)		(-1.82)
Loss * Favorite			-0.53%		-0.86%			-0.63%		-0.93%
			(-1.02)		(-1.64)			(-1.22)		(-1.78)
Win * Advanced stage				0.68%	0.51%				0.96%	0.82%
				(1.19)	(0.89)				(1.69)	(1.44)
Loss * Advanced stage				-1.38%	-1.40%				-1.42%	-1.46%
				(-2.41)	(-2.46)				(-2.52)	(-2.58)
R squared	0.087	0.097	0.096	0.097	0.118	0.081	0.089	0.089	0.094	0.111
N	627	627	627	627	627	627	627	627	627	627

Table 6 – Post-match returns

This table presents mean two-day raw and abnormal returns following games of publicly traded soccer clubs participating in Champions League and UEFA Cup competitions. Club *i*'s *Raw return* is equal to ($R_{i,0}+R_{i,1}$), where $R_{i,0}$ is club *i*'s stock return on game day and $R_{i,1}$ is the return on the following day. The market model for each club *i* in each calendar year, *T*, is estimated:

$$R_{i,t\subset T} = \alpha_{i,T} + \beta_{i,T} R_{LM,t} + \varepsilon_{i,t}$$

where $R_{i,t}$ is the daily return on stock *i* on day *t* belonging to year *T*, $R_{LM,t}$ is the value-weighted local market return, and $\varepsilon_{i,t}$ is the daily abnormal return. Club *i*'s *Abnormal return* is equal to ($\varepsilon_{i,0}+\varepsilon_{i,1}$). *Panel A* presents mean returns for the whole sample. *Panel B* separates the sample into home and away games. *Panel C* separates the sample into pre-game favorites and underdogs. *Panel D* segments the sample into early and advanced stage games. *Panel E* is restricted to elimination games. In parentheses, the table reports t-statistics for H_0: *mean(Return)=0*. *N* is the number of club-games in each subsample.

	Raw returns	Abnormal returns	N
Panel A - All games	-0.44%	-0.44%	627
	(-2.80)	(-2.82)	
Panel B - Home and away games			
Home games	-0.47%	-0.45%	313
	(-2.11)	(-2.05)	
Away games	-0.42%	-0.43%	314
	(-1.85)	(-1.94)	
Panel C - Favorites and underdogs			
Favorites	-0.39%	-0.40%	430
	(-2.13)	(-2.14)	
Underdogs	-0.55%	-0.52%	197
	(-1.84)	(-1.86)	
Panel D - Advanced and early stages			
Early stages	-0.24%	-0.27%	458
	(-1.36)	(-1.55)	
Advanced stages	-0.99%	-0.89%	169
	(-2.98)	(-2.71)	
Panel E - Advances and eliminations			
	-0.45%	-0.54%	195
	(-1.32)	(-1.60)	

Table 7 – Expected and realized game outcomes

This table presents summary statistics of expected and realized game outcomes. In *Panels A and B*, *Expected* is the mean ex-ante probability of a particular outcome implied from bookmaker odds and by pre-game betting exchange contracts, respectively. *In-sample* is the realized proportion of a particular outcome. In *Panel C*, *Exchanges* and *Bookmakers* correspond to the mean ex-ante probabilities as defined in *Panels A and B*, respectively. In *Panels A and B*, *Diff.* is the difference between *Estimated* and *In-sample*, whereas in *Panel C* is the difference between *Exchanges* and *Bookmakers*. In all panels, t-statistics for H_0: *Diff=0* are reported in parentheses. *N* is the number of club-games in each subsample.

Panel A – Bookmaker odds are obtained from Betexplorer (www.betexplorer.com), which compiles odds from various bookmakers and reports the best historical odds measure for each potential outcome. Odds are translated into probabilities of match outcomes, $Prob_{bookies,j}$, using the following transformation:

$$Prob_{bookies,win} = \frac{1/Odds_{win}}{1/Odds_{win} + 1/Odds_{draw} + 1/Odds_{loss}},$$

where $Prob_{bookies,win}$ is the ex-ante probability of a win implied by bookmakers' odds, and $Odds_{win}$, $Odds_{draw}$, and $Odds_{loss}$ are the bookmakers' odds of winning, tying, and losing, respectively.

Panel B - Bookmaker odds-based probabilities

	Win			Loss			
	Expected	In-sample	Diff.	Expected	In-sample	Diff.	N
All games	42.19%	42.02%	0.17%	31.66%	33.79%	-2.13%	583
			(0.08)			(-1.03)	
Home games	52.90%	54.83%	-1.93%	22.37%	21.38%	0.99%	290
			(-0.63)			(0.40)	
Away games	31.60%	29.35%	2.25%	40.85%	46.08%	-5.23%	293
			(0.81)			(-1.72)	
Favorites	48.35%	51.25%	-2.90%	26.08%	25.75%	0.33%	400
			(-1.10)			(0.14)	
Underdogs	28.74%	21.86%	6.88%	43.85%	51.37%	-7.51%	183
			(2.14)			(-1.94)	
Advanced stages	37.64%	28.86%	8.78%	34.27%	37.58%	-3.32%	149
			(2.24)			(-0.80)	
Early stages	43.76%	46.54%	-2.79%	30.76%	32.49%	-1.73%	434
			(-1.09)			(-0.73)	

Panel B – Betting exchange prices of contracts on wins, losses, and draws are from Betfair (www.betfair.com) and Tradesports (www.tradesports.com). To obtain the ex-ante probability of a game's outcome, first, we compute the volume-weighted average price of each type of contract matched prior to the start of the game (contracts that are "not in play"). We normalize prices using the sum of average prices on the three contracts. For example, the implied probability of a win, $Prob_{exchange,win}$, is computed as:

$$Prob_{exchange,win} = \frac{P_{win}}{P_{win} + P_{draw} + P_{loss}},$$

where P_{win}, P_{draw}, and P_{loss} are the average prices of win, draw, and loss contracts, respectively.

Panel A - Betting exchange probabilities

	Win			Loss			
	Expected	In-sample	Diff.	Expected	In-sample	Diff.	N
All games	43.44%	37.89%	5.55% (1.58)	30.87%	37.45%	-6.58% (-1.91)	227
Home games	54.66%	54.39%	0.27% (0.05)	20.87%	19.30%	1.57% (0.40)	114
Away games	32.14%	21.24%	10.90% (2.62)	40.95%	55.75%	-14.80% (-2.97)	113
Favorites	52.01%	48.00%	4.01% (0.92)	23.20%	28.00%	-4.80% (-1.24)	150
Underdogs	26.77%	18.18%	8.59% (1.83)	45.80%	55.84%	-10.04% (-1.68)	77
Advanced stages	34.50%	18.18%	16.32% (2.58)	37.92%	45.45%	-7.53% (-0.94)	44
Early stages	45.60%	42.62%	2.98% (0.75)	29.17%	35.52%	-6.35% (-1.66)	183

Panel C – This panel provides a direct comparison of match outcome ex-ante probabilities implied by betting exchange prices and bookmakers' odds when both are available.

Panel C - Comparison of bookmaker odds-based probabilities and betting exchange probabilities

	Win			Loss			
	Exchanges	Bookmakers	Diff.	Exchanges	Bookmakers	Diff.	N
All games	43.13%	38.60%	4.53% (2.47)	31.07%	35.36%	-4.30% (-2.57)	217
Home games	54.21%	48.27%	5.93% (2.61)	21.14%	26.62%	-5.48% (-3.22)	109
Away games	31.95%	28.84%	3.11% (1.50)	41.09%	44.19%	-3.10% (-1.38)	108
Favorites	51.90%	45.80%	6.10% (3.05)	23.20%	28.75%	-5.55% (-3.46)	142
Underdogs	26.52%	24.96%	1.56% (0.74)	46.07%	47.87%	-1.80% (-0.71)	75
Advanced stages	34.40%	32.20%	2.20% (0.70)	37.98%	39.60%	-1.62% (-0.49)	42
Early stages	45.22%	40.14%	5.09% (2.42)	29.41%	34.35%	-4.94% (-2.61)	175

Table 8 – Relation between expected and realized match outcomes

This table presents ordered logit estimates for the relation between game outcomes, ex-ante probabilities implied by betting exchange prices or bookmakers' odds, and game characteristics. The ordered logistic model estimated is:

$$\ln\left(\frac{prob\,(Y \le result\,)}{1-\,prob\,(Y \le result\,)}\right) = \alpha_{result} - \beta_{probwin}\ prob_{\ win} - \beta_{probdraw}\ prob_{\ draw} - \sum_{j} \beta_{j} I_{j}\ ,$$

where $Y=1$ for wins, $Y=2$ for draws, and $Y=3$ for losses, *result* takes on values 1 or 2, $prob_{win}$ ($prob_{draw}$) is the ex-ante probability of a win (draw) implied by betting exchange prices or bookmakers' odds as defined in Table 7, I_j are zero-mean indicator variables for home/away games, favorite/underdog status, and stage of the competition, similar to Table 5. P-values of the coefficient estimates' χ^2 under H_0: *Coefficient=0* are reported in parentheses. *N* is the number of unique games.

	Betting exchange probabilities					Bookmaker odds-based probabilities				
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Intercept 1	3.251	2.868	3.255	3.263	2.600	1.482	1.429	1.188	1.666	1.009
	(0.005)	(0.014)	(0.005)	(0.005)	(0.031)	(0.046)	(0.060)	(0.120)	(0.028)	(0.009)
Intercept 2	4.616	4.251	4.619	4.631	3.998	2.696	2.642	2.406	2.884	2.238
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.009)
Prob (win)	-6.715	-6.023	-6.721	-6.624	-5.387	-5.554	-5.449	-5.072	-5.548	-4.441
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Prob (draw)	-3.630	-3.332	-3.632	-3.770	-3.331	0.216	0.249	0.560	-0.488	0.206
	(0.263)	(0.306)	(0.263)	(0.249)	(0.313)	(0.922)	(0.910)	(0.799)	(0.829)	(0.928)
Home		-0.541			-0.696		-0.058			-0.283
		(0.085)			(0.057)		(0.777)			(0.236)
Favorite			0.005		-0.185			-0.319		-0.378
			(0.990)		(0.675)			(0.124)		(0.122)
Advanced stage				0.240	0.301				0.291	0.194
				(0.512)	(0.436)				(0.134)	(0.337)
N	211	211	211	211	211	555	555	555	555	555

Table 9 – Relation between (pre-match) expected outcome and realized (post-match) return

This table reports restricted and unrestricted OLS estimates of the relation between returns of publicly traded clubs following Champions League and UEFA Cup games and the ex-ante probabilities implied by betting exchange prices or bookmakers' odds. The following model is estimated:

$$R_i = \alpha + \beta_W W_i + \beta_{probwin}\ prob_{win,i} + \beta_D D_i + \beta_{probdraw}\ prob_{draw,i} + \varepsilon_i .$$

We estimate both the unrestricted model and the model that is subject to the following restrictions:

$$\beta_W = -\beta_{probwin};\ \beta_D = -\beta_{probdraw};\ \alpha = 0.$$

Ri is the club post-game raw or abnormal return as defined in Table 6, *Win* (*Draw*) is an indicator variable for wins (draws), and $prob_{win}$ ($prob_{draw}$) is the ex-ante probability of a win (draw) implied by betting exchange prices or bookmakers' odds as defined in Table 7. In the columns labeled *Unrestricted model*, *Wald statistic* and *p-value* provide the corresponding test statistics under H_0: *All coefficient restrictions hold*. *N* is the number of club-games.

	Betting exchange probabilities				Bookmaker odds-based probabilities			
	Unrestricted model		Restricted model		Unrestricted model		Restricted model	
	Raw returns [1]	Abnormal returns [2]	Raw returns [3]	Abnormal returns [4]	Raw returns [5]	Abnormal returns [6]	Raw returns [7]	Abnormal returns [8]
Intercept	-0.31%	-0.69%			-0.85%	-1.31%		
	(-0.26)	(-0.55)			(-0.60)	(-0.94)		
Win	2.30%	2.44%			3.05%	2.80%		
	(4.71)	(4.85)			(7.48)	(6.96)		
Draw	1.19%	1.32%			1.89%	1.91%		
	(2.47)	(2.66)			(4.40)	(4.51)		
Prob(win)	-2.09%	-2.21%			-2.46%	-1.87%		
	(-1.82)	(-1.87)			(-2.09)	(-1.60)		
Prob(draw)	-0.64%	0.03%			-1.45%	-0.18%		
	(-0.17)	(0.01)			(-0.35)	(-0.04)		
Win - Prob(win)			2.35%	2.56%			3.11%	2.87%
			(4.95)	(5.21)			(7.61)	(7.10)
Draw - Prob(draw)			1.22%	1.39%			1.97%	2.00%
			(2.59)	(2.86)			(4.58)	(4.70)
N	227	227	227	227	583	583	583	583
R squared	0.093	0.099			0.091	0.082		
Wald statistic	0.08	0.60			3.28	3.15		
p-value	(0.970)	(0.615)			(0.021)	(0.025)		

Table 10 – Expected and unexpected post-game returns controlling for likelihood of match outcome
This table reports "expected returns" around games. Expected returns account for biases in investors' estimates of game outcomes. Expected returns are computed as

$$E(R) = (prob_{win}^{\ obj} - prob_{win}^{\ subj})\frac{V_{win} - V_{loss}}{V_{before}} + (prob_{draw}^{\ obj} - prob_{draw}^{\ subj})\frac{V_{draw} - V_{loss}}{V_{before}},$$

Where the estimates of $\frac{V_{win} - V_{loss}}{V_{before}}$ and $\frac{V_{draw} - V_{loss}}{V_{before}}$ are given by the coefficients of the restricted model in (13). $prob_{win}^{\ obj}$ ($prob_{draw}^{\ obj}$) is the in-sample proportion of wins (draws). $prob_{win}^{\ subj}$ ($prob_{draw}^{\ subj}$) is the investors' subjective estimates of the likelihood of win (draw), obtained from the betting exchange prices. In addition, the table reports "adjusted returns", defined as the differences between mean realized returns and expected returns. Panel A presents mean expected and adjusted returns for the whole sample. Panel B separates the sample into home and away games. Panel C separates the sample into pre-game favorites and underdogs. Panel D segments the sample into early and advanced stage games. In parentheses, the table reports t-statistics for H_0: mean(Adjusted return)=0. *N* is the number of club-games in each subsample.

	Expected returns		Adjusted returns		
	Raw returns	Abnormal returns	Raw returns	Abnormal returns	N
Panel A - All games	-0.14%	-0.16%	-0.30%	-0.28%	627
			(-1.90)	(-1.81)	
Panel B - Home and away games					
Home games	0.02%	0.02%	-0.49%	-0.47%	313
			(-2.19)	(-2.14)	
Away games	-0.30%	-0.33%	-0.11%	-0.10%	314
			(-0.50)	(-0.43)	
Panel C - Favorites and underdogs					
Favorites	-0.10%	-0.11%	-0.29%	-0.29%	430
			(-1.57)	(-1.53)	
Underdogs	-0.22%	-0.24%	-0.33%	-0.28%	197
			(-1.10)	(-1.01)	
Panel D - Advanced and early stages					
Early stages	-0.11%	-0.12%	-0.13%	-0.15%	458
			(-0.74)	(-0.85)	
Advanced stages	-0.28%	-0.29%	-0.71%	-0.60%	169
			(-2.15)	(-1.82)	