Understanding Investor Sentiment: The Case of Soccer*

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Abstract

We examine whether investors' biased ex-ante beliefs regarding probability distributions of future event outcomes are partially responsible for instances of stock market's inefficient responses to resolutions of uncertainty. 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 in part 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-event abnormal returns. Our evidence may have important implications for firms' investment decisions and corporate control transactions.

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Abstract

We examine whether investors' biased ex-ante beliefs regarding the probability distribution of future events' outcomes can partially explain the stock market's inefficient response to resolution of uncertainty. In our experiment, we analyze stock returns of publicly traded European soccer clubs around important matches. Using a novel proxy for investors' expectations derived from contracts traded on betting exchanges (prediction markets), we find that in our sample investor sentiment is attributable in part 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-event abnormal returns. Our evidence may have important implications for firms' investment decisions and corporate control transactions.

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 irrational reactions or emotions while evaluating securities (see Hirshleifer (2001) for an excellent overview of psychological biases). Second, investors may have biased estimates of the distributions of firms' future cash flows (e.g., Baker and Wurgler (2006, 2007)). While the first type of investor sentiment has received substantial attention (e.g., Saunders (1993), Hirshleifer and Shumway (2003), Kamstra, Kramer and Levi (2000, 2003), Frieder and Subrahmanyam (2004), and Yuan, Zheng and Zhu (2005)), the effects of ex-ante biased beliefs on firm value has received relatively little attention, which may be due to the inherent difficulty of measuring investors' subjective expectations.

To examine whether investors' inability to correctly estimate probability distributions of event outcomes affects market prices, we focus on the stock price behavior of publicly traded sports clubs. This experimental design is desirable for at least two reasons. First, frequent, easily quantifiable, and value-relevant information signals have observable ex-ante (objective) expectations (e.g., Brown and Hartzell (2001)). Second, if investors occasionally react irrationally to resolution of uncertainty, sporting events would be an ideal setting for detecting such emotional reactions (e.g., Edmans, Garcia and Norli (2007)). Our tests rely on a novel proxy for investors' *subjective* beliefs and, different from earlier studies, show that sentiment is at least partially an ex-ante phenomenon, in the sense that investors are overly optimistic ex-ante and, thus, typically end up disappointed ex-post.

The distinction between the two manifestations of investor sentiment is important. Consider, for instance, firms' earnings announcements. Skinner and Sloan (2002) and Trueman, Wong and Zhang (2003) find that stock prices of growth firms, and of internet firms in particular, respond asymmetrically to earnings surprises. Specifically, average realized negative returns following negative surprises are significantly larger in magnitude than typical positive returns following positive surprises, a result that is not due to a more frequent occurrence of positive surprises. This evidence could be consistent with both types of investor sentiment. On the one hand, investors may be overly optimistic ex-ante, resulting in average negative returns following earnings announcements. On the other hand, even if investors have unbiased ex-ante beliefs about earnings realizations, their irrational ex-post reaction to earnings surprises may not be efficiently priced in before the announcements.

Notably, however, an asymmetric market response to earnings announcements could also occur in a world in which prices are efficient, both ex-ante and ex-post. Indeed, there is evidence that firms manage earnings to meet target thresholds (e.g. Degeorge, Patel, and Zeckhauser, 1999) and that market prices react sharply to even small negative earnings surprises. The possibility of firms purposely manipulating reported event outcomes may contaminate analyses of the sources of investor sentiment that are based on self-reported corporate events. Therefore, another major benefit of our experiment is that match outcomes are verifiable and *irreversible*, all but eliminating concerns that the market reaction to the resolution of uncertainty may be partially driven by investors' perception of potential manipulation.

Our study is related to the seminal work of Brown and Hartzell (2001), as well as studies by Palomino, Renneboog and Zhang (2005) and Renneboog and Van Brabant (2000) in that we analyze stock returns of sports franchises. We document a close-to-zero mean positive return following wins and significant mean negative returns after losses and draws. Importantly, similar to Brown and Hartzell (2001) and Edmans, Garcia and Norli (2007), we find that the unconditional mean post-event return is negative. The market reaction to game outcomes is clearly asymmetric: stock price changes following losses are substantially larger in magnitude than those following wins.

Brown and Hartzell (2001) and Edmans, Garcia and Norli (2007) suggest that the market's asymmetric reaction to match outcomes may be due to investors' optimism.[1] Yet, existing studies find no support for this conjecture (e.g., Brown and Hartzell (2001), Palomino, Renneboog and Zhang (2005), and Edmans, Garcia and Norli (2007)). These studies use winning and losing odds quoted by bookmakers as a proxy for investors' beliefs regarding game outcomes. However, there are reasons to believe that investors' expectations may not be well represented by odds quoted by bookmakers. First, bookmaker odds

[1] As Edmans, Garcia, and Norli (2007; p. 1991) explain: "...the reference point against which gains and losses are measured becomes an important determinant of utility. The natural reference point in our setting is that of supporters' pre-game expectations of how their team will perform. A number of studies show that fans are subject to an "allegiance bias," whereby individuals who are psychologically invested in a desired outcome generate biased predictions... Thus, if the reference point of soccer fans is that their team will win, we may find a greater stock price reaction after losses than after wins."

are generally found to be efficient predictors of game results (e.g., Sauer (1998)).[2] 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, reflect investors' subjective beliefs.

We argue that a better – albeit far from perfect – measure of investors' subjective expectations of game outcomes may be derived from the market price of related contracts traded on betting exchanges (prediction markets). To the best of our knowledge, this measure has not been used before.[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 soccer clubs' stocks. We argue that equilibrium prices of contracts traded in prediction markets are better aligned with investors' beliefs.[4] Importantly, since the betting exchange contracts that we use are very short-lived – most of them are matched on game-day – the risk-neutral probabilities of game outcomes implied by these contracts' prices should be nearly identical to physical probabilities of outcomes perceived by investors. Thus, one can use betting exchange prices to make inferences about investors' subjective beliefs.

Our results show that distinguishing between the probability distribution of match outcomes implied by bookmaker odds (objective probabilities hereafter) and that implied by betting exchange prices (subjective probabilities henceforth) is crucial in the analysis of investor sentiment. Based on tests employing bookmaker odds, we can reject the hypothesis that pre-event stock prices reflect expected post-game prices. Conversely, we cannot reject the hypothesis that pre-game stock prices equal expected post-game prices computed

[2] We discuss the efficiency of bookmaker odds in predicting game results in Section 6.

[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.

[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 6.

using investors' subjective (biased) probabilities of game outcomes - as implied by betting exchange prices. This finding is consistent with the idea that the apparent market inefficiency follows to some extent from investors' inability to assign correct probabilities to event outcomes.

This result is important because many important decisions taken by publicly traded firms are based in part on presumably efficient market values. Examples include real investments (e.g., Tobin (1969) and Hayashi (1982)), timing of mergers and acquisitions (e.g., Hackbarth and Morellec (2008) and Lyandres, Zhdanov and Hsieh (2008)), and corporate control decisions in general (e.g., Shleifer and Vishny (1986)).[5] Thus, understanding the evolution of stock prices around resolutions of uncertainty is crucial for firm value maximization.

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, unlike bookmaker odds, betting exchange prices often reflect an overly optimistic assessment of public teams' prospects. 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.

To summarize, the main contribution of this paper is twofold. First, we introduce a novel proxy for investors' beliefs about likelihoods of future event outcomes in order to examine the effects of biased investors' ex-ante expectations on the market's reaction to resolution of uncertainty. We argue that betting exchange prices are more closely related to investors' subjective expectations than bookmaker odds. 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

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

outcomes. While due to the nature of our proxy for investors' subjective beliefs, the scope of this study is limited to stocks of publicly traded sport franchises, a similar reasoning may be useful in other settings involving investors' inefficient responses to uncertainty resolutions.

The paper proceeds as follows. In the next section we provide an illustrative example of how the two sources of investor sentiment may affect securities prices. In Section 3 we describe the data and present summary statistics. Section 4 shows that sports performance and operating performance are related and, thus, game results may provide investors with important information about clubs' valuation. In Section 5 we examine the evolution of stock prices around games. We discuss our proxies for investors' subjective beliefs and objective probabilities of game outcomes, and various biases associated with them in Section 6. In Section 7 we incorporate investors' pre-game expectations into tests of post-game returns. We summarize our evidence and conclude in Section 8.

2 An illustrative example of ex-ante biased beliefs and ex-post emotional reactions

As mentioned above, Skinner and Sloan (2002) and Trueman, Wong and Zhang (2003) show that average realized negative returns following negative earnings surprises are significantly larger in magnitude than the typical positive returns following positive surprises, resulting in overall negative average market reaction to earnings announcements. In addition to potential earnings management, this finding could be due to investors' overly optimistic expectations of firms' earnings or investors' ex-post irrational reaction to resolutions of uncertainty. Carrying on an example based on this empirical finding, in this section we illustrate how the two alternative, non-mutually-exclusive sources of investor sentiment may affect stock prices around earnings announcements.

The difference between the two forms of investor sentiment are illustrated in Figure 1.

Insert Figure 1 here

Assume that a firm faces an event with an uncertain outcome. For simplicity, assume there are two possible realizations of post-event value, V_{1G} and V_{1B} , which occur with probabilities p and $1-p$ respectively, where $V_{1G} > V_{1B}$. Figure 1a depicts the base-case scenario in which investors have unbiased expectations and respond rationally to uncertainty resolutions. In this case, firm's pre-event value, V_0, equals expected post-event value, $\mathbb{E}(V_1) = pV_{1G} + (1-p)V_{1B}$. Assume now that investors are overly optimistic, in the sense that they believe that the probability of the good outcome, V_{1G}, is $q > p$. In that case, depicted in Figure 1b, $V_0 = \mathbb{E}_q(V_1) > \mathbb{E}(V_1)$, i.e. pre-event value, which equals the expectation of post-event value under investors' subjective probability distribution, $\mathbb{E}_q$, is higher than expected post-event value under the true probability distribution. As a result, the expected change in value around the event is negative.

Now consider a third scenario, depicted in Figure 1c, in which investors assign correct probabilities to event outcomes but react emotionally to the resolution of uncertainty, i.e. their post-event valuations, V'_{1G} and V'_{1B} are different from true post-event values, V_{1G} and V_{1B}, these differences not being reflected in pre-event value, V_0. (In the particular case depicted in Figure 1c, investors overreact to both good and bad outcomes, but more so to the bad one). Note that similar to the case presented in Figure 1b, the expected change in value around the event can be negative.

Under the scenario depicted in Figure 1b, referred to as "immediate emotions" (see Loewenstein (2000)), firms' post-announcement market values are efficient, while pre-announcement values are inefficient. Under the scenario shown in Figure 1c, referred to as "anticipated emotions", pre-event values are efficient, while post-event ones are not.

3 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 that have participated in at least one game in either the Champions League or the UEFA Cup during this period, ranging from such powerhouses as Manchester United, Juventus and Ajax, to virtually unknown teams such as Danish clubs Aalborg and Silkeborg.[6] Our sample teams played in 595 unique matches, 31 of which featured two publicly traded clubs, corresponding to 626 observations.

[6] 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

We choose to concentrate on international games, rather than national championships or cups, for several reasons. First, we hypothesize and show empirically that games in European competitions are very important for clubs' profitability and valuation. Second, the UEFA Cup and the 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.)[7] Third, as discussed in the introduction, we use bookmaker 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. Finally, while national leagues' games generally take place during the weekend posing a potential weekend-effect problem, UEFA Cup and Champions League games are played between Tuesdays and Thursdays.[8]

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

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

[7]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. All of the results reported below are robust to excluding group-stage matches from the sample.

[8]National cups' games are played on weekdays. Cup games, however: have arguably small economic consequences; are most important for the smaller teams, which are uncommon in our sample of publicly traded clubs; and suffer from the data limitation explained above.

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 third column. Large soccer nations – England, Italy, and Portugal – comprise more than 60% of the sample.

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 sixth column. The next column presents the number of games played in advanced stages of European competitions.[9] 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 eighth 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. Team 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.[10]

The next six columns report 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

[9] 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.

[10] 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.

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 next three columns present the number of games in which betting exchange data, bookmaker odds data, and both are available. Betting exchange prices are available for about one third of the sample.

The four rightmost columns in Table 1 report soccer clubs' book and market values and 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 game by 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 pre-game market capitalizations 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.[11] 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%.

4 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 four measures of clubs' sports performance. The first one is the number of games played in the European competitions during the year. Due to the knock-

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

out 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 a 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 club has played at least one game in the Champions League during the year because participation in this competition is more lucrative and, thus, expected to have a larger positive impact on teams' fortunes. The fourth measure is the team's UEFA rating.

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 four performance measures above. The regression is estimated using club fixed effects. Standard errors are clustered by firm, as in Petersen (2008).[12] The results are presented in Table 2.

Insert Table 2 here

Profitability is clearly related to sports performance. The coefficients on all performance measures are significantly positive at the 5% level. More importantly the economic impact of a club's successful performance in 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

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

association between sports and operating performance does not necessarily imply that game results provide information to investors that is important enough to trade on. To begin our analysis of this question, we compare the trading volume on days following games and on game days to the typical off-game trading volume.

We obtain daily number of shares traded for each club from Datastream and define abnormal trading volume, $AVOLUME_{i,t}$, 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 game days or days following games, and $VOLUME_{i,t-5}$ is the trading volume five trading days earlier. 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 $VOLUME_{i,t-5}$ 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 trading volumes around game days are presented in Table 3.

Insert Table 3 here

The trading volume of soccer clubs' stocks appears to be abnormally high on game days as well as on days following games. The mean volume on game days is 25% higher than on off-game days and the mean volume on days following games is 39% higher than the off-game-day volume, both differences being highly significant. Abnormal trading volume on days following games is large and significant following wins and losses, but less so 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 elimination games than following non-elimination games (70% higher than off-game volume and 30% higher than off-game volume respectively) and, in the former subset, volume following eliminations is typically larger than following advances, consistent with eliminations providing more information than advances to next rounds.

These results are consistent with the evidence in Brown and Hartzell (2001), who report that the trading volume of Boston Celtics Partnership shares increases following games.

Thus, similar to professional basketball, soccer games provide new information on which investors trade. Notably, however, the trading volume is also abnormally high during game days, but only when the eventual outcome is not a draw. Similarly, abnormal volume is larger during game-days in which the eventual result is elimination than when a team ends up advancing to the next round. In the next section we examine the magnitudes of the market's responses to new information contained in game outcomes and relate the results on game-day and next-day trading volumes to stock returns.

5 Game outcomes and returns

A soccer club's profitability and value is related to its sports performance (see Table 2). Furthermore, investors seem to trade on the information conveyed by 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. Although we focus our analysis on stock returns following games, we also document some interesting patterns in game-day returns, which we discuss at the end of this section.

5.1 Returns on days following games

We compute abnormal returns following games[13] by estimating the market model for each club each year:

$$R_{i,t\in T} = \alpha_{i,T} + \beta_{1_{i,T}} R_{LM,t} + \beta_{2_{i,T}} R_{LM,t-1} + \beta_{3_{i,T}} R_{i,t-1} + \varepsilon_{i,t}, \tag{3}$$

where $R_{i,t\in T}$ is the daily return on stock i on day t belonging to year T, $R_{LM,t}$ ($R_{LM,t-1}$) is the value-weighted (lagged) local market index return, $R_{i,t-1}$ is stock i's previous-day return, and $\varepsilon_{i,t}$ is the resulting estimate of daily abnormal return.[14] We estimate the market model on an annual basis because we conjecture and confirm empirically that the intercept in (3) 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

[13] All the results below hold for raw returns.

[14] We include lagged market returns to account for the fact that some soccer clubs' shares are thinly traded. Lagged individual stock returns are included to account for possible autocorrelations.

stable.[15] Table 4 reports post-game abnormal returns when the sample is partitioned into wins, losses, and draws.[16]

Insert Table 4 here

We start the analysis by examining the returns for the whole sample. Importantly, wins result in statistically insignificant average abnormal returns of 0.15%, while losses and draws generate highly significant average returns of -2.2% and -0.9% respectively. The differences between the market reaction to wins, losses, and draws, reported in columns 4 and 5, are statistically significant and economically large.

We further segment the sample by 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 is close to zero and statistically insignificant, while the one following away wins is a marginally significant 0.6%. For the same reason, losses on home turf have a larger impact than losses away from home, -3% versus -1.8%. Next, we separate 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 on home/away games, the market is not overly surprised when favorites win - the mean return is close to zero and insignificant, whereas wins by underdogs convey important positive information - the mean abnormal return is a significant 1.1%. Losses by underdogs are greeted less unfavorably than losses by favorites (mean returns of -1.6% for underdogs and -2.7% for favorites).

Next, we separate the sample by stage of the competition, into early and advanced. Consistent with games at later stages having larger value consequences, we find that the magnitude of returns after both wins and losses is larger after games in advanced stages than in early ones. Finally, 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

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

[16] The significance of 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.

are higher than returns following wins. Returns following eliminations are slightly larger in magnitude than returns following losses. Because the results for wins/draws/losses and advances/eliminations are by no means independent, however, these differences likely underestimate the impact of advances to the next round and of eliminations.

Large stock price changes following 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 well be consistent with 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 be significantly different from zero. The last column of Table 4 reports the average post-game return for the whole sample, as well as for various subsamples. Importantly, the mean post-game return is negative and highly significant across all subsamples, and is largest in magnitude for games played in advanced stages of European competitions. This finding is clearly a challenge for market efficiency. We examine it closely in the next section.

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:

$$R_{i,k} = \alpha + \beta_{win} W_{i,k} + \beta_{loss} L_{i,k} + \sum_j \beta_{win\_j} I_{j,i,k} W_{i,k} + \sum_j \beta_{loss\_j} I_{j,i,k} L_{i,k} + \varepsilon_{i,k}, \quad (4)$$

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 (4) as the mean return following draws, we normalize $I_{j,i,k}$ to have zero means.[17] Table 5 presents the results of estimating (4).

Insert Table 5 here

Column 1 of Table 5 confirms the results in Table 4: relatively neutral outcomes – draws – are followed by significantly negative returns, returns following wins are significantly

[17] 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.

higher than those following draws, and losses are accompanied by negative returns that are significantly larger in magnitude than post-draw returns. This asymmetric return pattern, manifested by negative returns following draws, near-neutral reactions to wins, and large negative returns after losses, is consistent with the findings of Brown and Hartzell (2001) and Edmans, Garcia and Norli (2007).

The results reported in column 2 show that home losses are associated with larger negative returns than away losses, which are more likely ex-ante, the difference being highly significant. 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 on returns.

5.2 Game-day returns

Table 6 presents returns on game days. Its layout is the same as that of Table 4.

Insert Table 6 here

As evident from the last column of Table 6, the mean return on game day is positive, 0.5%, and highly statistically significant. Furthermore, the mean game-day return is positive and significant in all subsamples except for the sample of teams that are underdogs ex-ante. There are two potential non-mutually-exclusive explanations for non-zero game-day returns. First, some information related to the eventual match outcome may become available before the game itself (i.e. coaches releasing information about starting lineups and players' injuries; teams' preparedness to games gradually becoming public knowledge). It is not obvious, however, why positive news would be released consistently more frequently on game-days than negative news. Therefore, the information hypothesis may not fully explain the documented positive game-day returns.

Second, as argued in Trueman, Wong and Zhang (2003) and Liang (1999), investor optimism could generate price pressure as a result of large demand for the clubs' stocks in anticipation of uncertainty-resolving events. This price pressure explanation may be sensible in our setting given that soccer clubs' stocks are relatively thinly traded and in light of the systematic investors' optimism that seemingly characterizes our sample teams, as documented in the next section. In what follows, we examine these two potential reasons for the puzzling game-day returns.

The fact that game-day abnormal trading volume is higher for games with more informative outcome (wins and losses relative to draws, and eliminations relative to advances to next round; see Table 3) is seemingly consistent with a leakage of result-relevant information on game-days. Further analysis, however, does not support this interpretation. First, the typical game-day returns in Table 6 do not follow the ordering implied by information-based hypothesis (i.e. returns on days during which games are tied are higher than those during days in which a public team wins). Second, untabulated results show that (subjective) odds typically move against our sample teams on game days, which is inconsistent with the idea that the typical flow of information released to market participants is positive on game days.[18] Moreover, the correlation between game-day returns and changes in estimated winning and losing probabilities during game-days is virtually zero. Third, in the subsample of 31 games in which both teams are public, the two teams experience game-day returns of the same sign in 16 cases and, among these, both returns are positive in 13 cases. This is inconsistent with new information arrival since positive news for one team should be regarded as negative for the rival team. Finally, the correlation between game-day return and eventual outcome is not significantly different from zero.

The evidence seems to be more supportive of the price pressure hypothesis. First, there is a statistically significant, positive correlation of 13% between game-day abnormal volume and abnormal return, while the correlation between game-day volume and the absolute value of game-day return is an insignificant 6%. If there were no new information released on game days, buying pressure would lead to a positive correlation between volume and returns. If there were no price pressure and all trading was a result of new information, one would expect a positive correlation between volume and absolute returns. Thus, the volume-return correlation is more consistent with the price pressure hypothesis. Second, there is a statistically significant, negative correlation of -11% between game-day returns and following day returns, consistent the existence of partial reversal of price-pressure-driven game-day returns on the following day and inconsistent with information leakage

[18] Investors' subjective estimates of winning probabilities drop by 2.4% on average on game days, while their estimates of losing probabilities increase by 2.1%. Please see the discussion of our proxy for investors' subjective beliefs in the next section.

on game-days.

Overall, the evidence suggests that at least part of the positive mean game-day returns is due to price pressure created by overly optimistic investors. Since such price pressure is likely to be partially reversed following resolutions of uncertainty, we control for game-day returns in our analysis of the causes of large negative returns following games, which is presented in the next two sections.

6 Proxies for investors' beliefs and objective probabilities

Behavioral finance literature offers two explanations for the inefficient stock price reaction to game results documented in the previous section. First, investors may set prices based on unbiased beliefs of conditional post-game club values, yet systematically misestimate the likelihood of various outcomes. If investors are too optimistic about publicly traded clubs' chances to succeed, on average, they will 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 reaction, as in the case of national team matches in Edmans, Garcia and Norli (2007). In this section and the next one we concentrate on the effects of investor ex-ante biased beliefs on stock returns. Specifically, in this section we examine the extent of investors' optimism and in Section 7 we quantify the effects of this optimism on expected post-game returns.

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 the potential biases associated with them.

6.1 Bookmaker odds as a proxy for objective probabilities

The proxy for the likelihoods of sporting events' outcomes that is most widely used in the literature 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)).[19]

Bookmaker odds are generally found to be unbiased predictors of game outcomes (see Sauer (1998) for a survey of wagering markets literature).[20] For this reason, 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 582 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:

$$prob_{win}^{obj} = \frac{1/O_{win}}{1/O_{win} + 1/O_{draw} + 1/O_{loss}}, \tag{5}$$

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.

Insert Table 7 here

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 losing odds (32% expected versus 34% realized). When analyzing various subsamples, however, it appears that bookmakers have biased expectations in some cases. For instance, there is substantial bias when teams are ranked higher than their opponents: on average,

[19] An alternative proxy 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 in-sample fitted values and bookmaker odds is above 90%. This is also the case in our sample.

[20] 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.

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)). Yet, pre-event securities' prices should reflect investors' (subjective) beliefs about the distribution of post-event prices rather than true (i.e. objective) probabilities of possible realizations of uncertainty. However, 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.

6.2 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 Benfica Lisbon in a Champions League game and paying nothing otherwise.[21] 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 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, weighed by traders' wealth. They also show that for other specifications of traders' utilities, prediction market prices

[21] 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.

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 ranked higher than their opponents, a fact also consistent with a larger fan base.[22] 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. As a result, although we expect public teams' fans to typically dominate the trading in prediction markets, betting exchange prices likely provide an estimate of public team investors' beliefs that is biased towards objective probabilities.

Assumption 3: There are limits to arbitrage between betting exchanges and bookmakers

[22] Consistent with the assertion that better teams have larger fan bases, the differences between subjective and objective expectations are larger for favorites than for underdogs (see Panel C of Table 7) below. In addition, the differences between subjective and objective expectations are larger for teams with larger market values (this result is available upon request).

If traders on betting exchanges monitor odds posted by bookmakers,[23] betting exchange prices are not likely to deviate from prices derived from bookmakers odds by more than the difference of 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, typically, a difference of up to 5% between betting exchange prices and bookmakers odds can not be arbitraged away and may persist. Furthermore, trading on betting exchanges may have additional 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 higher 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)), and 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

[23] There is some empirical evidence to the contrary. For example, Palomino, Renneboog and Zhang (2005) report that investors do not seem to pay attention to releases of bookmaker odds.

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 outcome (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 game outcomes to 483, corresponding to 161 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 40 more games, increasing our betting exchange prices sample to 211 games.[24,25]

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

$$prob_{win}^{subj} = \frac{P_{win}}{P_{win} + P_{draw} + P_{loss}}, \tag{6}$$

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.

On average, investors that trade on betting exchanges are overly optimistic about their teams' prospects. They assign an average probability of 44% (30%) to a win (loss), while the in-sample proportion of wins (losses) is 37% (38%). The differences between expected

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

[25] Games featuring two public teams clearly violate Assumption 2 above. Thus, in the 16 games featuring two public teams, we only include the favorite team in the sample, with the idea that favorites are more likely to have larger fan bases than underdogs.

and realized outcomes are marginally significant. Except for the case of teams playing on home turf, the mean differences 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 34% implied by exchange prices is significantly different from the realized proportion of wins of 13%. Furthermore, investors are grossly overoptimistic about the winning chances of underdogs (27% expected versus 16% realized) and of teams playing away from home (33% 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 203 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 44%, 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 when they 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 game outcomes 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:

$$\ln\left(\frac{prob(Y_i \leq result)}{1 - prob(Y_i \leq result)}\right) = \alpha_{result} - \beta_{prob_{win}} prob_{win} - \beta_{prob_{draw}} prob_{draw} - \sum_j \beta_j I_{j,i}, \quad (7)$$

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 $prob_{win}^{subj}$ and $prob_{draw}^{subj}$, in the case of betting exchange-based probabilities, or the values of $prob_{win}^{obj}$ and $prob_{draw}^{obj}$, 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 (4). Table 8 presents the estimates of (7). 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. Panel A of Table 8 presents the results for the samples of games in which bookmaker odds and betting exchange prices are available separately. Panel B displays the results for the sample of games in which both proxies for objective and subjective probabilities are available. Columns 1 and 2 in each panel examine biases in the exchange-based probabilities, while columns 3-4 present the results for the bookmaker odds-based probabilities.

Insert Table 8 here

Not surprisingly, both $prob^{subj}_{win}$ and $prob^{obj}_{win}$ 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 8, the coefficient estimates for home games suggest a marginally significant "home bias" when using the exchange-based probabilities. The regressions using bookmaker-odds-based probabilities reveal no statistically significant biases. 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 market reaction to event outcomes.

7 Returns adjusted for expected outcomes

The evidence in the previous section 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 contribute to the negative mean return following soccer games.

If investors set a club's stock price prior to a game, V_0, as the weighted average of post-game values, with weights equal to their subjective probabilities of game outcomes, then V_0 can be expressed as

$$V_0 = prob^{subj}_{win} V_{win} + prob^{subj}_{draw} V_{draw} + (1 - prob^{subj}_{win} - prob^{subj}_{draw}) V_{loss}, \tag{8}$$

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

$$R = \frac{V_{win}W + V_{draw}D + V_{loss}L - V_{before}}{V_{before}} + \varepsilon =$$
$$\frac{(V_{win} - V_{loss})}{V_{before}}W + \frac{(V_{draw} - V_{loss})}{V_{before}}D -$$
$$\frac{(V_{win} - V_{loss})}{V_{before}}prob_{win} - \frac{(V_{draw} - V_{loss})}{V_{before}}prob_{draw} + \varepsilon, \tag{9}$$

where W, D, and L are indicator variables for wins, draws, and losses, respectively, and ε is a zero-mean error term. (9) provides the means to test whether pre-game prices are determined 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

$$R_i = \alpha + \beta_W W_i + \beta_{prob_{win}} prob_{win,i} + \beta_D D_i + \beta_{prob_{draw}} prob_{draw,i} + \varepsilon_i, \tag{10}$$

must satisfy the set of restrictions:

$$\beta_W = -\beta_{prob_{win}},\ \beta_D = -\beta_{prob_{draw}},\ \alpha = 0. \tag{11}$$

There is one difficulty in estimating (11). The cross-sectional variation in draw probability, $prob_{draw,i}$, is very low. (Both subjective and objective probabilities of tying a game are around 25% for nearly all games.) Thus, in order to achieve identification, we estimate the following variant of (10), in which we incorporate the restriction $\beta_D = -\beta_{prob_{draw}}$:

$$R_i = \alpha + \beta_W W_i + \beta_{prob_{win}} prob_{win,i} + \beta_{draw}(D_i - prob_{draw,i}) + \varepsilon_i. \tag{12}$$

The set of restrictions in (12) is

$$\beta_W = -\beta_{prob_{win}},\ \alpha = 0. \tag{13}$$

In order to account for the large negative correlation between game-day returns and returns on days following games, which is likely due, at least in part, to the reversal of game-day price pressure, as previously discussed, we modify the regression in (12) by augmenting it with day-zero return, $R_{0,i}$:[26]

$$R_i = \alpha + \beta_W W_i + \beta_{prob_{win}} prob_{win,i} + \beta_{draw}(D_i - prob_{draw,i}) + R_{0,i} + \varepsilon_i. \tag{14}$$

[26] All the results below are insensitive to whether (12).is augmented by day-zero return.

The estimates of the unrestricted model in (14) 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.

Insert Table 9 here

Panel A of Table 9 presents the results of estimating (14) and testing the set of restrictions in (13) for samples of games for which bookmaker odds and betting exchange probabilities are available separately. In columns 1-2, we estimate model (14) using betting exchange-based probabilities. The results of the "unrestricted model" in column 1 are consistent with the hypothesis that the market's inefficient response to match outcomes follows from biases in investors' ex-ante beliefs. The intercept is close to zero, suggesting that the market does not react to expected losses. The estimates of β_W and $\beta_{prob_{win}}$ are of the same order of magnitude and they have positive and negative signs, respectively, implying that expected wins result in relatively mild negative market reactions. The Wald test reported at the bottom of column 1 fails to reject the set of restrictions in (13).

In column 2, we examine a "semi-restricted" model, in which we impose a restriction $\beta_W = -\beta_{prob_{win}}$:

$$R_i = \alpha + \beta_{win}(W_i - prob_{win,i}) + \beta_{draw}(D_i - prob_{draw,i}) + \varepsilon_i, \tag{15}$$

and test the hypothesis $\alpha = 0$. Rejection of this hypothesis would indicate that potential biases in investors' beliefs cannot explain the abnormally low returns following games. The results of estimating (15) are presented in column 2. First, the intercept is not significantly different from zero. Second, the results provide an estimate of the economic importance of differentiating between subjective and objective probabilities: 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 2.5 basis points.

The inability to reject the set of restrictions in (13) in the restricted model and the restriction on the intercept in the semi-restricted model 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 (14).

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 3-4 of Panel A we estimate models (14) and (15) 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 in column 3, the set of restrictions in (13) can be comfortably rejected at any confidence level, as evidenced by near-zero p-values. Therefore, the tests 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. The evidence in column 4 is also illustrative of the differences between investors' subjective and objective probabilities. The intercept is significantly negative, implying that pre-game stock prices do not equal objective expectations of post-game prices.

One potential reason for the ability to reject the set of restrictions in (13) when using bookmaker-odds-implied probabilities but not when using betting-exchange-based ones could be the different compositions of the samples of games with available betting exchange prices data and bookmaker odds data and the sizes of these samples. To address this issue, in Panel B of Table 9 we re-estimate the regressions above using the sample of 203 games for which both objective and subjective probabilities are available. The results in Panel B are similar to those discussed above in that the restrictions can be comfortably rejected in a model that uses bookmaker odds but not in a model that uses betting exchange prices. Similarly, the intercept in the semi-restricted model in (15) is significantly negative when bookmaker odds data are being used, while it is insignificantly different from zero when betting exchange prices are used.

The evidence in this section supports the idea that investors' inability to correctly anticipate game outcomes is at least partially responsible for the significantly negative mean abnormal return following European soccer matches. However, it is important to emphasize that 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. By design, our tests aim to isolate the portion of post-game returns that is due to investors' overly optimistic expectations of game outcomes. Such tests do not allow us to draw inferences regarding the effects of post-game emotional reactions on post-game returns.

8 Conclusions

We investigate the effect of biased ex-ante estimates of probabilities of future event outcomes on stock returns of publicly traded European soccer clubs around important matches. Consistent with past studies of securities prices' reaction to sporting events (e.g., Brown and Hartzell (2001) and Edmans, Garcia and Norli (2007)), we find that the market reaction to soccer games' outcomes is asymmetric. Losses are associated with significantly negative post-game returns, while wins are followed by near-zero returns. Overall, the mean return following games is significantly negative. This finding suggests that the market does not react efficiently to the outcome of soccer games played by publicly traded clubs.

While a sample of publicly traded soccer teams provides a particularly convenient experimental setting for examining the sources of investor sentiment, distinguishing between the two types of sentiment that drive the market's inefficient response to resolution of uncertainty – biased ex-ante expectations and emotional ex-post reactions to event outcomes – 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 before or after uncertainties are resolved can facilitate decision making and enhance firm value.

We introduce a new proxy for investors' beliefs that is based on prices of contracts traded on betting exchanges and argue that this measure is more closely related to investors' subjective expectations than measures based on bookmaker odds. The tests based on our novel measure suggest 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 resolutions of the uncertainty.

Although 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 different 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 market efficiency and enhance firms' value-maximizing decision making.

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Figure 1: Biases in ex-ante beliefs and irrational ex-post reactions: An illustration

This figure presents three scenarios. In Figure 1a, investors' ex-ante beliefs are unbiased and ex-post reactions are rational. In Figure 1b, investors beliefs are biased, but ex-post reactions are rational. In Figure 1c, investors' beliefs are unbiased, but they overreact to good and bad outcomes ex-post.

Figure 1a

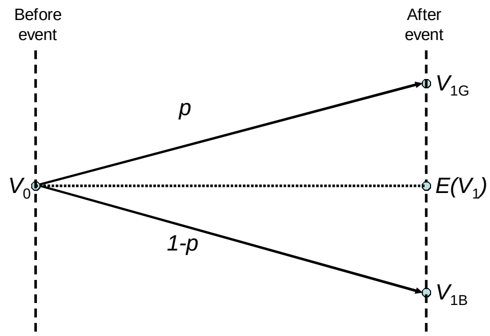

Figure 1b

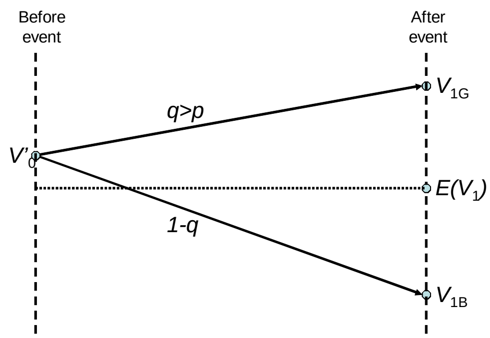

Figure 1c

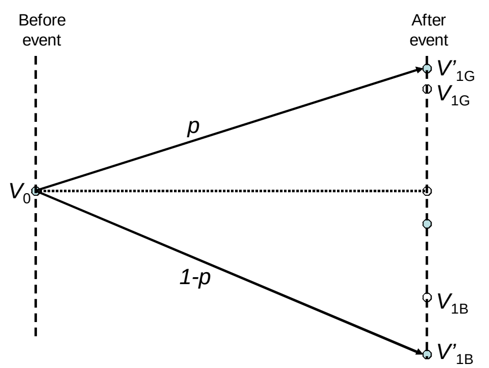

Table 1 – Match statistics, market values, and operating performance measures of publicly traded soccer clubs

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 scored:received* is the mean number of own versus opponent goals. *Games with betting exchange prices* and/or *games with bookmaker odds* denote the number of games with available variables. 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.

Panel A - By team							Match statistics									Market values and performance measures			
[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]
Team	Country	# Games	Champ. League	Against public teams	Deciding	Advanced stages	Home	As favorites	% wins	% losses	% advance	Goals scored: received	With exchange prices	With bookmaker odds	With Both	Market Cap ($MM)	Sales ($MM)	Assets ($MM)	ROA
Aalborg	Denmark	6	0	0	3	0	3	2	16.7%	50.0%	33.3%	0.67:1.5	4	3	3	9.06	12.63	22.87	0.09
Ajax	Holland	50	44	0	13	10	25	26	34.0%	34.0%	46.2%	1.32:1.08	30	48	30	130.88	63.66	116.92	0.17
Aston Villa	England	2	0	0	1	0	1	2	50.0%	50.0%	0.0%	1.5:1.5	0	2	0	26.60	52.71	101.92	0.10
Besiktas	Turkey	32	6	0	11	2	15	16	34.4%	40.6%	63.6%	1.47:1.25	14	29	12	111.58			
B. Dortmund	Germany	35	27	0	10	11	16	28	45.7%	31.4%	58.3%	1.46:1.17	0	33	0	89.00	95.27	219.93	0.16
Brondby	Denmark	21	9	2	10	0	10	14	33.3%	42.9%	40.0%	1.24:1.24	4	19	3	34.24	16.29	59.07	0.11
Celtic	Scotland	52	26	2	19	7	27	26	48.1%	36.5%	63.2%	1.69:1.17	10	49	10	35.63	83.43	126.17	0.08
Fenerbahce	Turkey	13	11	0	3	0	6	0	23.1%	69.2%	0.0%	1.31:2.31	13	13	13	250.89			
Galatasaray	Turkey	21	17	0	6	3	11	15	23.8%	47.6%	16.7%	1.05:1.33	7	19	7	76.25			
Juventus	Italy	51	51	4	15	25	25	35	51.0%	31.4%	66.7%	1.57:1.04	29	50	29	254.72	202.38	464.48	0.20
Lazio	Italy	52	34	4	14	16	26	50	42.3%	32.7%	62.5%	1.56:1.23	8	50	8	175.14	98.31	440.34	0.08
Man. United	England	81	81	4	19	36	41	76	54.3%	21.0%	57.1%	1.83:0.91	27	71	26	897.26	222.84	368.01	0.23
Millwall	England	2	0	0	1	0	1	2	0.0%	50.0%	0.0%	1:2	2	2	2	15.64	11.71	32.79	-0.18
Newcastle	England	35	14	2	13	12	18	21	60.0%	25.7%	69.2%	1.86:1.26	12	29	10	79.40	137.07	291.52	0.13
Porto	Portugal	75	52	7	25	29	37	53	38.7%	32.0%	66.7%	1.41:1.07	16	73	16	41.51	28.42	97.40	0.10
Roma	Italy	56	30	3	16	12	28	38	39.3%	28.6%	52.9%	1.3:1.05	17	53	17	129.45	113.44	322.40	0.21
Silkeborg	Denmark	2	0	0	1	0	1	0	0.0%	100.0%	0.0%	0.5:2.5	0	2	0	0.88	5.08	7.68	0.11
Southampton	England	2	0	0	1	0	1	2	0.0%	50.0%	0.0%	0.5:1	0	2	0	19.09	64.07	102.55	0.21
Sporting	Portugal	36	9	3	13	5	20	22	41.7%	36.1%	53.3%	1.61:1.44	16	34	16	42.07			
Trabzonspor	Turkey	2	2	0	1	0	1	2	50.0%	50.0%	0.0%	1:1.5	2	1	1	90.39			

Panel B - By country

	Match statistics														Market values and performance measures			
[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]
Country	# Games	Champ. League	Against public teams	Deciding	Advanced stages	Home	As favorites	% wins	% losses	% advance	Goals scored: received	With exchange prices	With bookmaker odds	With Both	Market Cap ($MM)	Sales ($MM)	Assets ($MM)	ROA
Denmark	29	9	2	14	0	14	16	27.6%	48.3%	35.7%	1.07:1.38	8	24	6	26.73	14.92	49.90	0.11
England	122	95	6	35	48	62	103	54.1%	23.8%	56.8%	1.8:1.04	41	106	38	619.50	189.38	331.85	0.19
Germany	35	27	0	10	11	16	28	45.7%	31.4%	58.3%	1.46:1.17	0	33	0	89.00	95.27	219.93	0.16
Holland	50	44	0	13	10	25	26	34.0%	34.0%	46.2%	1.32:1.08	30	48	30	130.88	63.66	116.92	0.17
Italy	159	115	11	45	53	79	123	44.0%	30.8%	60.4%	1.47:1.11	54	153	54	184.57	137.02	406.54	0.16
Portugal	111	61	10	38	34	57	75	39.6%	33.3%	61.9%	1.48:1.19	32	107	32	41.69	28.42	97.40	0.10
Scotland	52	26	2	19	7	27	26	48.1%	36.5%	63.2%	1.69:1.17	10	49	10	35.63	83.43	126.17	0.08
Turkey	68	36	0	21	5	33	33	29.4%	48.5%	38.1%	1.29:1.49	36	62	33	126.68			

Panel C - All

Match statistics														Market values and performance measures			
[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]
# Games	Champ. League	Against public teams	Deciding	Advanced stages	Home	As favorites	% wins	% losses	% advance	Goals scored: received	With exchange prices	With bookmaker odds	With Both	Market Cap ($MM)	Sales ($MM)	Assets ($MM)	ROA
626	413	31	195	168	313	430	42.5%	33.4%	55.3%	1.5:1.17	211	582	203	208.39	114.39	261.90	0.15

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. 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 Asset in year t			
	[1]	[2]	[3]	[4]
Intercept	0.0833 (3.55)	0.0973 (4.07)	0.091 (3.89)	0.058 (2.14)
Participated in Champions League in year t	0.0921 (2.94)			
Qualified to advanced stage of competition in year t		0.0765 (2.39)		
Number of games played in year t			0.006 (2.15)	
UEFA Rating in year t				0.0012 (3.18)
R^2	0.582	0.551	0.543	0.592
# obs.	93	93	93	93

Table 3 – Trading volume and volatility around game days

This table 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 game-days and days following games and $VOLUME_{i,t-5}$ is the trading volume 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 or $VOL_{i,t-10}$. 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.

	Game day	Following day	# obs
All games	24.50% (3.92)	38.78% (5.80)	522
Wins	25.13% (2.71)	39.34% (3.79)	220
Draws	8.66% (0.68)	24.95% (1.89)	127
Losses	35.21% (3.14)	47.43% (4.08)	175
Deciding games	37.14% (3.62)	70.44% (5.96)	174
Advances	23.19% (1.56)	54.16% (3.19)	91
Eliminations	52.44% (3.77)	87.91% (5.41)	83
Non-deciding games	18.18% (2.32)	30.00% (2.88)	348

Table 4 – Post-match returns by game outcome

This table presents mean abnormal returns following games won, lost, or tied by publicly traded soccer clubs participating in Champions League and UEFA Cup competitions. The market model for each club *i* in each calendar year, *T*, is estimated as

$$R_{i,t\subset T} = \alpha_{i,T} + \beta_{1,i,T} R_{LM,t} + \beta_{2,i,T} R_{LM,t-1} + \beta_{3,i,T} R_{i,t-1} + \varepsilon_{i,t},$$

where $R_{i,t}$ is the daily return on stock *i* on day *t* belonging to year *T*, $R_{LM,t}$ ($R_{LM,t-1}$) is the (lagged) value-weighted local market return, $R_{LM,t-1}$ is lagged daily return on stock *i*, and $\varepsilon_{i,t}$ is the daily abnormal return. The columns under *Wins* (*Draws*, *Losses*) correspond to Champions League and UEFA Cup games won (tied, lost) by a sample club. In parentheses, the table reports t-statistics for H_0: *mean(Return)=0*. *N* is the number of club-games in each subsample. Columns *Wins minus Losses* and *Draws minus Losses* report the respective differences with t-statistics for the differences in parentheses. Column *All* refers to the full sample.

	Wins	Draws	Losses	All	Win-Loss	Draw-Loss
	0.15%	-0.89%	-2.18%	-0.88%	2.33%	1.29%
All games	(0.80)	(-4.64)	(-9.26)	(-6.90)	(7.75)	(4.27)
	266	151	209	626		
Home and away games						
	-0.08%	-1.32%	-3.04%	-0.98%	2.95%	1.72%
Home games	(-0.34)	(-4.77)	(-5.99)	(-5.16)	(5.28)	(2.98)
	173	76	64	313		
	0.58%	-0.45%	-1.80%	-0.77%	2.38%	1.35%
Away games	(1.94)	(-1.76)	(-7.21)	(-4.58)	(6.12)	(3.78)
	93	75	145	313		
Favorites and underdogs						
	-0.05%	-0.85%	-2.66%	-0.91%	2.61%	1.81%
Favorites	(-0.24)	(-3.97)	(-7.93)	(-5.98)	(6.67)	(4.56)
	219	100	111	430		
	1.08%	-0.96%	-1.63%	-0.81%	2.70%	0.66%
Underdogs	(2.30)	(-2.52)	(-5.09)	(-3.48)	(4.78)	(1.33)
	47	51	98	196		
Advanced and early stages						
	0.00%	-0.63%	-1.74%	-0.70%	1.73%	1.11%
Early stages	(-0.01)	(-2.78)	(-7.28)	(-5.02)	(5.41)	(3.36)
	212	98	148	458		
	0.75%	-1.36%	-3.24%	-1.37%	3.99%	1.89%
Advanced stages	(2.08)	(-4.02)	(-6.01)	(-4.87)	(6.15)	(2.96)
	54	53	61	168		
	Advanced		Eliminated	All	Adv-Elim	
	0.17%		-2.41%	-1.05%	2.58%	
Deciding games	(0.63)		(-5.59)	(-3.99)	(5.09)	
	103		92	195		

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 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*.

	[1]	[2]
Intercept	-0.89% (-3.60)	-0.89% (-3.70)
Win	1.03% (3.37)	1.32% (4.23)
Loss	-1.29% (-4.01)	-1.74% (-5.21)
Win * Home		-0.68% (-1.81)
Loss * Home		-1.44% (-3.21)
Win * Favorite		-1.06% (-2.23)
Loss * Favorite		-1.35% (-3.27)
Win * Advanced stage		0.61% (1.36)
Loss * Advanced stage		-1.57% (-3.50)
R squared	0.1004	0.1555
# obs	626	626

Table 6 – Game-day returns

This table presents mean abnormal game-day returns for games won, lost, or tied by publicly traded soccer clubs participating in Champions League and UEFA Cup competitions. The market model for each club *i* in each calendar year, *T*, is estimated as

$$R_{i,t\subset T} = \alpha_{i,T} + \beta_{1,i,T} R_{LM,t} + \beta_{2,i,T} R_{LM,t-1} + \beta_{3,i,T} R_{i,t-1} + \varepsilon_{i,t},$$

where $R_{i,t}$ is the daily return on stock *i* on day *t* belonging to year *T*, $R_{LM,t}$ ($R_{LM,t-1}$) is the (lagged) value-weighted local market return, $R_{LM,t-1}$ is lagged daily return on stock *i*, and $\varepsilon_{i,t}$ is the daily abnormal return. The columns under *Wins* (*Draws*, *Losses*) correspond to Champions League and UEFA Cup games won (tied, lost) by a sample club. In parentheses, the table reports t-statistics for H_0: *mean(Return)=0*. *N* is the number of club-games in each subsample. Columns *Wins minus Losses* and *Draws minus Losses* report the respective differences with t-statistics for the differences in parentheses. Column *All* refers to the full sample.

	Wins	Draws	Losses	All	Win-Loss	Draw-Loss
	0.48%	0.79%	0.22%	0.47%	0.26%	0.57%
All games	(3.64)	(3.11)	(1.15)	(4.47)	(1.13)	(1.79)
	266	151	209	626		
Home and away games						
	0.54%	0.92%	0.12%	0.55%	0.42%	0.80%
Home games	(3.44)	(2.70)	(0.39)	(4.02)	(1.22)	(1.73)
	173	76	64	313		
	0.37%	0.66%	0.27%	0.39%	0.11%	0.40%
Away games	(1.54)	(1.74)	(1.11)	(2.45)	(0.32)	(0.88)
	93	75	145	313		
Favorites and underdogs						
	0.46%	0.78%	0.48%	0.54%	-0.02%	0.30%
Favorites	(3.15)	(2.41)	(2.26)	(4.53)	(-0.07)	(0.79)
	219	100	111	430		
	0.60%	0.82%	-0.07%	0.32%	0.67%	0.89%
Underdogs	(1.81)	(1.98)	(-0.21)	(1.52)	(1.44)	(1.68)
	47	51	98	196		
Advanced and early stages						
	0.45%	0.79%	0.19%	0.44%	0.27%	0.60%
Early stages	(3.65)	(2.39)	(0.85)	(3.81)	(1.07)	(1.52)
	212	98	148	458		
	0.60%	0.80%	0.31%	0.56%	0.30%	0.49%
Advanced stages	(1.37)	(2.01)	(0.78)	(2.36)	(0.50)	(0.89)
	54	53	61	168		
	Advanced		**Eliminated**	**All**	**Adv-Elim**	
	0.91%		0.08%	0.52%	0.82%	
Deciding games	(3.11)		(0.31)	(2.57)	(2.06)	
	103		92	195		

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 A - Bookmaker odds probabilities

	Wins			Losses			
	Expected	In-sample	Diff.	Expected	In-sample	Diff.	# obs
All games	42.24% (57.72)	42.10% (20.55)	0.15% (0.07)	31.60% (49.10)	33.85% (17.24)	-2.24% (-1.09)	582
Home and away games							
Home games	52.90% (61.24)	54.83% (18.73)	-1.93% (-0.63)	22.37% (35.97)	21.38% (8.86)	0.99% (0.40)	290
Away games	31.66% (40.09)	29.45% (11.02)	2.21% (0.79)	40.77% (49.17)	46.23% (15.82)	-5.46% (-1.80)	292
Favorites and underdogs							
Favorites	48.35% (60.26)	51.25% (20.48)	-2.90% (-1.10)	26.08% (42.20)	25.75% (11.76)	0.33% (0.14)	400
Underdogs	28.82% (29.85)	21.98% (7.14)	6.84% (2.12)	43.75% (39.66)	51.65% (13.90)	-7.90% (-2.04)	182
Advanced and early stages							
Advanced stages	37.80% (30.55)	29.05% (7.76)	8.75% (2.22)	34.08% (29.12)	37.84% (9.46)	-3.76% (-0.90)	148
Early stages	43.76% (50.00)	46.54% (19.42)	-2.79% (-1.09)	30.76% (40.37)	32.49% (14.44)	-1.73% (-0.73)	434
Deciding games	45.08% (16.34)	42.22% (11.44)	2.86% (0.62)	30.10% (11.92)	35.56% (9.94)	-5.46% (-1.25)	180

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 B - Betting exchange probabilities

	Wins			Losses			
	Expected	In-sample	Diff.	Expected	In-sample	Diff.	# obs
All games	43.90% (30.58)	36.97% (11.10)	6.93% (1.91)	30.48% (23.61)	38.39% (11.44)	-7.90% (-2.20)	211
Home and away games							
Home games	55.16% (31.00)	52.83% (10.84)	2.33% (0.45)	20.57% (15.71)	20.75% (5.24)	-0.19% (-0.04)	106
Away games	32.53% (19.95)	20.95% (5.25)	11.58% (2.69)	40.49% (23.00)	56.19% (11.55)	-15.70% (-3.03)	105
Favorites and underdogs							
Favorites	52.00% (33.33)	46.85% (11.19)	5.14% (1.15)	23.27% (18.50)	28.67% (7.56)	-5.40% (-1.35)	143
Underdogs	26.87% (16.05)	16.18% (3.60)	10.70% (2.23)	45.66% (22.57)	58.82% (9.78)	-13.17% (-2.08)	68
Advanced and early stages							
Advanced stages	34.12% (13.53)	13.16% (2.37)	20.96% (3.44)	38.25% (14.20)	50.00% (6.08)	-11.75% (-1.36)	38
Early stages	46.05% (28.46)	42.20% (11.21)	3.85% (0.94)	28.78% (20.12)	35.84% (9.80)	-7.06% (-1.80)	173
Deciding games	47.06% (16.60)	45.00% (6.95)	2.06% (0.29)	28.60% (11.32)	31.67% (5.23)	-3.07% (-0.47)	60

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 - Bookmaker odds-based probabilities vs. betting exchange probabilities						
	Wins			Losses			
	Expected	In-sample	Diff.	Expected	In-sample	Diff.	# obs
All games	43.51% (30.02)	38.74% (31.48)	4.77% (2.51)	30.73% (23.43)	35.24% (31.37)	-4.51% (-2.61)	203
Home and away games							
Home games	54.66% (30.12)	48.48% (32.60)	6.18% (2.63)	20.86% (15.48)	26.48% (23.45)	-5.62% (-3.20)	102
Away games	32.24% (19.82)	28.90% (20.61)	3.35% (1.56)	40.70% (22.90)	44.09% (29.29)	-3.39% (-1.46)	101
Favorites and underdogs							
Favorites	51.89% (32.86)	45.64% (34.22)	6.24% (3.02)	23.21% (18.29)	28.94% (26.96)	-5.73% (-3.45)	135
Underdogs	26.87% (16.05)	25.02% (16.34)	1.85% (0.82)	45.66% (22.57)	47.74% (26.37)	-2.08% (-0.77)	68
Advanced and early stages							
Advanced stages	34.43% (13.39)	32.43% (14.53)	2.00% (0.59)	37.92% (13.81)	39.34% (17.23)	-1.42% (-0.40)	37
Early stages	45.53% (27.77)	40.14% (28.68)	5.39% (2.50)	29.13% (19.98)	34.32% (27.07)	-5.20% (-2.69)	166
Deciding games	46.37% (16.31)	43.86% (6.61)	2.51% (0.35)	28.96% (11.24)	31.58% (5.08)	-2.62% (-0.39)	57

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. *Panel A* presents results for the samples of games with available betting exchange and bookmaker data separately. *Panel B* presents the results for the unified sample with both betting exchange and bookmaker data available.

	Panel A: All games			
	Betting exchange probabilities		Bookmaker odds-based probabilities	
Intercept 1	3.296 (0.005)	2.736 (0.025)	1.482 (0.046)	1.009 (0.009)
Intercept 2	4.671 (0.000)	4.145 (0.001)	2.696 (0.000)	2.238 (0.009)
Prob (win)	-6.748 (0.000)	-5.558 (0.000)	-5.554 (0.000)	-4.441 (0.000)
Prob (draw)	-3.713 (0.255)	-3.520 (0.291)	0.216 (0.922)	0.206 (0.928)
Home		-0.649 (0.078)		-0.283 (0.236)
Favorite		-0.104 (0.816)		-0.378 (0.122)
Advanced stage		0.381 (0.329)		0.194 (0.337)
# obs	582	582	211	211

	Panel B: Restricted sample			
	Betting exchange probabilities		Bookmaker odds-based probabilities	
Intercept 1	3.205 (0.007)	2.621 (0.037)	1.393 (0.314)	0.830 (0.152)
Intercept 2	4.596 (0.000)	4.049 (0.001)	2.746 (0.048)	2.233 (0.152)
Prob (win)	-6.658 (0.000)	-5.491 (0.000)	-6.661 (0.000)	-4.990 (0.001)
Prob (draw)	-3.563 (0.286)	-3.303 (0.336)	2.177 (0.628)	1.788 (0.711)
Home		-0.614 (0.097)		-0.413 (0.158)
Favorite		-0.092 (0.838)		-0.259 (0.556)
Advanced stage		0.317 (0.425)		0.342 (0.401)
# obs	203	203	203	203

Table 9 – Relation between (pre-match) expected outcome and realized (post-match) return
This table reports unrestricted and semi-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 unrestricted model is as follows::

$$R_i = \alpha + \beta_W W_i + \beta_{probwin}\ prob_{win,i} + \beta_{draw}(D_i - prob_{draw,i}) + R_{0,i} + \varepsilon_i .$$

The associated set of restrictions that we test are:

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

The semi-restricted model is as follows::

$$R_i = \alpha + \beta_{win}(W_i - prob_{win,i}) + \beta_{draw}(D_i - prob_{draw,i}) + R_{0,i} + \varepsilon_i .$$

The associated restriction is $\alpha = 0$. R_i is the club post-game abnormal return as defined in Table 4, *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.

	Panel A: All games			
	Betting exchange probabilities		Bookmaker odds-based probabilities	
	Unrestricted model	Semi-restricted model	Unrestricted model	Semi-restricted model
Intercept	-0.02% (-0.05)	-0.16% (-1.06)	-0.50% (-1.58)	-0.83% -6.76
Win	2.49% (5.36)		2.98% (9.50)	
Prob(win)	-3.25% (-3.31)		-3.78% (-4.81)	
Win - Prob(win)		2.45% (5.31)		2.95% 9.43
Draw - Prob(draw)	1.13% (2.31)	1.06% (2.20)	1.69% (5.09)	1.67% 5.04
Day-0 abnormal return	-7.19% (-0.62)	-8.23% (-0.72)	-13.30% (-2.94)	-13.88% 3.08
R squared # obs	15.81% 211	15.36% 211	14.80% 582	14.60% 582
Wald statistic p value	2.54 (0.082)		23.54 (0.000)	

	Panel B: Restricted Sample			
	Betting exchange probabilities		Bookmaker odds-based probabilities	
	Unrestricted model	Semi-restricted model	Unrestricted model	Semi-restricted model
Intercept	-0.07% (-0.16)	-0.12% (-0.82)	-0.19% (-0.43)	-0.48% -2.66
Win	2.51% (5.29)		2.43% (5.11)	
Prob(win)	-3.08% (-3.06)		-3.19% (-2.71)	
Win - Prob(win)		2.48% (5.26)		2.39% 5.06
Draw - Prob(draw)	1.08% (2.17)	1.03% (2.10)	1.06% (2.11)	0.99% 2.01
Day-0 abnormal return	-8.76% (-0.75)	-9.41% (-0.81)	-9.08% (-0.77)	-9.71% -0.83
R squared # obs	16.24% 203	15.99% 203	15.27% 203	1495.00% 203
Wald statistic p value	1.87 (0.158)		3.81 (0.024)	