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# ABNORMAL RETURNS OF SOCCER TEAMS AND EVENT CLUSTERING: REASSESSING THE INFORMATIONAL VALUE OF BETS




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# Abnormal Returns of Soccer Teams and Event Clustering: Reassessing the Informational Value of Bets

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**Abstract** We analyse the links between soccer match results, bets and stock returns of all listed European soccer teams. Using an event study approach, we measure abnormal returns following wins, ties and losses. Wins are associated with positive abnormal returns, and ties and losses with negative abnormal returns. Additionally, we analyse the role of bets in shaping market reactions to unexpected results, which we find to be non-significant. We propose an alternative econometric approach, using seemingly unrelated regression models, to take into account the problem of overlapping events. While our results concerning match results are confirmed, abnormal returns following unexpected results are found to be statistically significant and to magnify the positive (negative) effects of wins (losses).

***Keywords*** *Information and Market Efficiency; Event Studies; Soccer; Bets; Event Clustering; Seemingly Unrelated Regression Equation (SUR)*

***JEL Classification*** *G14; L83; C30*

# 1 Introduction

In the last twenty years, several studies have suggested an association between sport events and individual mood: fans usually experience a strong positive reaction when their team performs well and a strong negative reaction when their team performs poorly. More specifically, wins are generally associated with improvements in mood and self-esteem (Hirt et al. 1992). Instead, losses are linked to increases in heart attacks, crimes and suicides (White 1989; Trovato 1998; Wann 2001; Carroll et al. 2002; Berthier and Boulay 2003; Chi and Kloner 2003).

Other studies have found a relationship between investor mood and stock prices. Several contributions in the behavioral finance literature investigate the effect of mood and investor sentiment on asset prices. Remarkable examples are Barberis et al. (1998), Daniel et al. (1998), and Baker and Wurgler (2006).[1]

A number of authors were able to join these two streams of the literature and show that soccer matches may influence stock returns. Ashton et al. (2003) find a strong association between the performance of the England soccer team and the general stock market index returns. Using international soccer results as a mood variable, Edmans et al. (2007) find an economically and statistically significant market reaction to losses, but not to wins. Brini and Palomba (2011) find a relationship between the stock returns of Italian soccer teams, their sport performances in terms of match outcomes, and the importance of the matches.

Recent studies (Palomino et al. 2009; Scholtens and Peenstra 2009; Bell et al. 2011; Bernile and Lyandres 2011) consider the information content of pre-match bets in studying the relationship between soccer match results and soccer team market returns.[2] Using a sample of soccer teams listed on the London Stock Exchange, Palomino et al. (2009) find a strong market reaction to match results and a lack of reaction to betting odds. They conclude that this lack of reaction may be due to

[1] A review of this stream of the literature can be found in Hirshleifer (2001) and Shiller (2000).

[2] The use of pre-match bets as an indicator of match uncertainty is quite common in the applied literature (e.g., see Czarnitzki and Stadtmann 2002).

the lack of informational content of betting information. Scholtens and Peenstra (2009), in a multi-country analysis over the period 2000–04, find similar results with regard to betting odds. Using bets as a proxy for investor expectations, Bernile and Lyandres (2011) analyse the returns of a sample of listed European soccer teams around important matches. They find that investors are overly optimistic about their teams' prospects *ex ante*, and disappointed *ex post*. This result leads to negative post-event abnormal returns. Bell et al. (2011) analyse a sample of English football teams between 2000 and 2008 and find that pre-match betting odds have an informational value.

Our paper aims to contribute to the above stream of literature. In particular, we analyse the relationship between soccer match results, bets and stock returns of all listed European soccer teams. Since sport events affect mood, expected and unexpected soccer match results provide a unique way of studying the link between investor mood and stock market prices. Our analysis aims to answer several questions:

i. First, by splitting the matches between wins, ties and losses, we wonder if these events lead to a different market reaction.

ii. Second, we test whether the intensity of the result, as measured by goal difference, has an effect on listed soccer team returns.

iii. Third, we ask ourselves whether the location where a match is played (at home or away) influences market reaction.

iv. Fourth, we test if any type of competition or date (year and month) effect influences the market reaction following wins, ties and losses.

v. Finally, using betting data, we divide all match results into expected and unexpected, and test whether the unexpected ones are associated with a larger effect on listed soccer team returns. According to the efficient market hypothesis, the stock prices of soccer team should reflect all the available information, including the one on expected results, which is implicit in the pre-match betting odds. Using this interpretation framework, only unexpected events may be expected to generate abnormal returns.

Our main findings show positive abnormal returns following wins and negative abnormal returns following both ties and losses. This result is consistent to controlling for the location where the match is played, the type and the date of competition. Furthermore, using the information of pre-match betting odds, we show that abnormal returns are magnified by unexpected results.

Our paper contributes to the existing literature in several respects:

i. The data we employ allow us to corroborate known results with new empirical evidence and to offer new insights on the effect of moods on soccer team stock prices.

ii. The existing literature focuses on national and international matches in single countries, or on international matches in several countries. Instead, our dataset includes all national and international match results of all 23 listed European soccer teams, in the three-year period 2007–09. These teams play in nine national championships and in all of UEFA's[3] international competitions, and represent the entire population of the listed soccer teams.[4]

iii. The role of betting is analysed only in recent studies. These studies consider the information content of the bets market as a proxy for investor expectations, and provide controversial results. Our data set includes the pre-match betting odds of all 23 listed European soccer teams and allows us to deepen the empirical evidences on their information content.

iv. As a robustness analysis, we use an alternative econometric methodology to the traditional event-study approach. Event studies generally deal with non-overlapping events, for which it is reasonable to assume that abnormal returns on individual securities are uncorrelated. However, soccer matches are played in the same days, thus the non-overlapping hypothesis no longer holds. To accommodate this problem of so-called 'event clustering' (Kolari and

[3] UEFA is the Union des Associations Européennes de Football.

[4] Although these 23 soccer teams represent the entire population of listed soccer teams, they are clearly just a small part of all European soccer teams.

Pynnönen 2010; Himmelmann and Schiereck 2012), we apply a seemingly unrelated regressions (SUR) model, which allows the covariances between abnormal returns to be non-null. Our results shows that the problem of overlapping events cannot be ignored.

The remainder of this paper is organized as follows: Section 2 describes the data set; Section 3 presents our hypotheses and modeling framework; Section 4 shows the results of our event study analysis; in Section 5, we retest some of our hypotheses using SUR; finally, Section 6 provides some conclusions.

## 2 Variable description and descriptive statistics

We base our empirical analysis on a unique data set we collected from the archives of SNAI (Società Nazionale Agenzie Ippiche), the leading sports betting agency in Italy. Our data set includes all the results and the pre-match betting odds of 2,157 matches played by all 23 of the listed soccer teams in Europe in the period 2007–09. In Appendix A, we report useful information on the teams considered. Related market data and market index returns are collected from Datastream.

In Table 1, we propose a short description of the variables we use in our empirical analysis.

## 3 Hypotheses and modeling framework

We use a standard event-study methodology (Campbell et al. 1997) to examine the behavior of the teams' stock returns around matches, that is, the events. The response variable used in all regression models is $Ar_{ij}$.[5]

[5] We use the event-parameter approach (also known as regression-based approach). This approach produces results that are numerically equivalent to the standard event-study method à la Brown and Warner (1980, 1985). Our results are based on heteroskedasticity-consistent standard errors and are double checked by constructing bootstrap confidence intervals. The latter are constructed using the procedure described in Greene (2007), by carrying out (with replacement) 5,000 samples from the full sample of observations.

**Table 1** Description of variables

| | |
|---|---|
| **Abnormal returns** | |
| $Ar_{ij}$ | is the percentage abnormal return of the soccer team *i* following its *j*th match, defined as $Ar_{ij} = r_{ij} - r_{mj}$, where $r_{ij}$ is the logarithmic return of the soccer team *i* for match *j*, and $r_{mj}$ is the logarithmic market return (represented by the STOXX® Europe 600 index[6]) at the same date. We consider a market-adjusted return to take into account the systematic component of stock returns.[7] |
| **Match result** | |
| $Win_{ij}$, $Tie_{ij}$, $Loss_{ij}$ | are three dummy variables indicating if soccer team *i* won, tied, or lost its *j*th match.[8] Of 2,157 matches considered, 1,088 are wins (50%), 519 are ties (24%) and 550 are losses (26%). The prevalence of wins on losses and ties shows that listed teams generally belong to the upper tier of their respective national leagues. |
| **Delta score** | |
| $Delta_{ij}$ | is the goal difference of team *i* in match *j*, defined as the goals scored by team *i* minus the goals scored by its opponent. This variable assumes positive, negative, or null values when the soccer team *i* wins, loses, or ties the match respectively. $Delta_i$ exhibits a symmetric distribution with an average (median) value of 0.54 (1) and a minimum (maximum) of –8 (8). Extreme positive or negative values of this variable (less than –5 or more than 5) are very rare (0.74 per cent of the observations). |
| **Site of competition** | |
| $Away_{ij}$, $Home_{ij}$ | are two dummy variables indicating if the soccer team *i* played the *i*th match away or at home. 1,085 (50%) matches were played at home and 1078 (50%) away. |
| **Type of competition** | |
| $Ncha_{ij}$, $Clea_{ij}$, $Uefa_{ij}$, $Icup_{ij}$, $Ncup_{ij}$ | are a set of dummy variables indicating the type of competition played by the soccer team *i* in match *j*. 1,663 (76.88 per cent) of competitions are national championship matches, 144 (6.66 per cent) are Champions League matches, 128 (5.92 per cent) are UEFA Cup matches, 12 (0.55 per cent) other international competition matches, and 216 (9.99 per cent) are national cup matches. |

[6] Using country-specific market indices might seem more appropriate if we consider that an investor is more likely to invest in her country. This hypothesis, called home bias, is often justified by the tendency of individuals to invest in what they believe to know better. To take this point into account, we recalculate all abnormal returns using country-specific indices as a robustness check. However, the results are not qualitatively different from the ones reported in the paper.

[7] In the CAPM framework, our procedure would imply a constant beta of 1 for all teams within the sample period. This assumption simplifies the analysis when the estimation window overlaps with some confounding effects. As a matter of the fact, if we were to estimate the betas for each soccer team, our estimates would be inflated by the effect of the previous week's match results. Using an SUR approach, as we do in the second part of the paper, we relax the assumption of unit beta for each soccer team.

[8] All the dummies are equal to one in correspondence of the first trading day following the match. If the match is played during the week, the first available trading day is the day following the match. If the match is played during the weekend, the first available trading day is on Monday. For this reason, we performed a time-series empirical test for the "Monday effect" before performing our event study. Our results, suggest us to reject the hypothesis of "Monday effect" in our data. Additional information on this test are available from the authors on request.

| | |
|---|---|
| **Year of competition** | |
| $Y07_{ij}$, $Y08_{ij}$, $Y09_{ij}$ | are a set of year dummies. Of the total number of matches, 1,062 were played in 2008 (49 per cent of the total), 566 in 2007 (26 per cent), and 529 in 2009 (25 per cent). |
| **Month of competition** | |
| $Jan_{ij}$, $Feb_{ij}$, $Mar_{ij}$, $Apr_{ij}$, $May_{ij}$, $Jun_{ij}$, $Jul_{ij}$, $Aug_{ij}$, $Sep_{ij}$, $Oct_{ij}$, $Nov_{ij}$, $Dec_{ij}$ | are a set of month dummies. The number of matches analysed is almost uniformly distributed across months (about 8 per cent per month). The only exceptions are the summer months, when less matches are played. |
| **Expected and unexpected results** | |
| $Exp_{ij}$, $Une_{ij}$ | are two dummy variables indicating if the result of match *j* of team *i* was expected or unexpected, based on the information of the latest pre-match betting odds. The match result with the highest probability of occurrence is considered an expected event, while the remaining two possible results are taken as unexpected. 952 out of 2,157 match results are unexpected (44 per cent of the total): 142 are unexpected wins (13 per cent of wins), 519 are unexpected ties (100 per cent of ties), and 291 are unexpected losses (53 per cent of losses). Therefore, while all ties are unexpected,[9] about 90 per cent of wins are expected, while 47 per cent of losses are expected. |

We start from a basic model analysing market reaction following wins, ties and losses. The related model equation is

$$\mathrm{AR}_{ij} = \alpha_1 \mathrm{Win}_{ij} + \alpha_2 \mathrm{Tie}_{ij} + \alpha_3 \mathrm{Loss}_{ij} + \varepsilon_{ij}, \tag{1}$$

where i = 1, …, 23 identifies the *i*th team, and $j = 1, \ldots, J_i$ is the *j*th match played by the *i*th team. It should be noted that max(*j*) takes on a different value for each team.

In this model, $\alpha_1$, $\alpha_2$ and $\alpha_3$ measure the average abnormal returns following wins, ties and losses, respectively. Coherently with previous findings in the theoretical and empirical literature, we formulate hypothesis $H_1$:

- $H_1$: $\alpha_1 > 0$, $\alpha_2 \cong 0$, $\alpha_3 < 0$, and $|\alpha_1| < |\alpha_3|$.

Our first hypothesis predicts positive abnormal returns following wins, and negative abnormal returns following losses, but no abnormal returns following ties. Furthermore, given the well-known

[9] Since a tie is the most probable result when teams are equally skilled, the absence of unexpected ties may indicate a disparity of skills between listed and unlisted soccer teams. However, this notion is merely speculative, thus future research might consider investigating this issue.

asymmetric reaction associated with positive and negative events, we expect the abnormal returns following losses to be greater in absolute terms than those following wins. All the predictions of $H_1$ are motivated by the effect of moods on stock prices.

As a further step, we test whether the intensity of the result, as measured by goal difference, has a (possibly nonlinear) effect on abnormal returns. To do so, we employ the following model:

$$AR_{ij} = \alpha + \delta_1 Delta_{ij} + \delta_2 Delta_{ij}^2 + \varepsilon_{ij}. \qquad (2)$$

In this model, $\mathrm{d}AR_{ij} / \mathrm{d}Delta_{ij} = \delta_1 + 2\delta_2 Delta_{ij}$ is the marginal effect of the goal difference on the abnormal returns. In this regard, we formulate the following hypothesis:

- $H_2$: $\delta_1 > 0,\ \delta_2 < 0,$ and $|\delta_1| > |\delta_2|$.

If market reaction is driven by mood, we expect abnormal returns to increases less than proportionally with the goal difference, that is, the positive mood associated with a win gradually decreases as $Delta_i$ increases.[10]

A third concern that may arise is whether the location where a match is played (at home or away) influences abnormal returns. To answer this question, we estimate the following model:

$$\begin{aligned} AR_{ij} = {} & \alpha_1 Win_{ij} \times Away_{ij} + \alpha_2 Tie_{ij} \times Away_{ij} + \alpha_3 Loss_{ij} \times Away_{ij} + \\ & \alpha_4 Win_{ij} \times Home_{ij} + \alpha_5 Tie_{ij} \times Home_{ij} + \alpha_6 Loss_{ij} \times Home_{ij} + \varepsilon_{ij}. \end{aligned} \qquad (3)$$

In this model, $\alpha_1$, $\alpha_2$ and $\alpha_3$ measure the average abnormal returns following wins, ties and losses when the soccer team $i$ plays the $j$th match away; $\alpha_4$, $\alpha_5$ and $\alpha_6$ measure the average abnormal returns following wins, ties and losses in home matches. We postulate hypothesis $H_3$:

- $H_3$: $\alpha_1 > \alpha_4 > \alpha_2 > 0,$ and $\alpha_6 < \alpha_3 < \alpha_5 < 0.$

We expect an away win to produce a larger positive abnormal return than a home win or an away tie. Conversely, we expect a home loss to cause larger negative abnormal returns than an away loss or tie. Indeed, wins, away or at home, and away ties are generally perceived as good news, while

[10] In a recent article, Beck and Meyer (2012) use goal difference as the outcome of a soccer match. The motivation for their decision is that marginal performance variations might be reflected by variations in observed goal differences.

losses, at home or away, and home ties are commonly considered disappointing. Playing at home is expected to provide an advantage, because the team can benefit from the support of its fans.

We also check if any type or date (year and month) of competition influences the abnormal returns following wins, ties and losses. To answer this question, we estimate four regression models (one for each effect) – not reported here to preserve space – by interacting the match result dummies with the type of competition, year, and month dummies. Joint Wald tests on the difference of the coefficients associated with one effect should evidence any influence on abnormal returns, if present. In what follows, we briefly state the hypotheses associated with these regression models.

- $H_4$: The type of competition played by the soccer team *i* in the *j*th match ($Ncha_{ij}$, $Clea_{ij}$, $Uefa_{ij}$, $Icup_{ij}$, $Ncup_{ij}$), has an effect on the magnitude of abnormal returns following wins, ties and losses.

Since not all types of competition are equally important, we expect a significant Wald test associated with this model (e.g., Champions League matches are generally considered more important than UEFA Cup matches, and can elicit larger market reactions).

- $H_5$: The year of competition in which the match takes place ($Y07_{ij}$, $Y08_{ij}$, $Y09_{ij}$) has an effect on the magnitude of abnormal returns following wins, ties and losses.

We test this hypothesis (and the following one) as a robustness check. If there were any systematic difference in the abnormal returns registered in different years, we could expect to find a significant year effect in our analysis.

- $H_6$: The month in which the *j*th match of team *i* takes place ($Jan_{ij}$, $Feb_{ij}$, $Mar_{ij}$, $Apr_{ij}$, $May_{ij}$, $Jun_{ij}$, $Jul_{ij}$, $Aug_{ij}$, $Sep_{ij}$, $Oct_{ij}$, $Nov_{ij}$, $Dec_{ij}$) has an effect on the magnitude of the abnormal returns following wins, ties and losses.

The period of the year in which the match takes place (beginning or end of the season) may have an effect on fan mood and, thus, on abnormal returns (e.g., the final match of the UEFA Champions League, which is one of the most important events for the soccer fans, is played in May or June).[11]

The last hypothesis that we test concerns the market reaction following expected and unexpected match results. According to the efficient market hypothesis, the market value of the soccer teams should incorporate all available information and react to match results only if they are unexpected. The equation of the estimated model is

$$\begin{aligned} AR_{ij} = {} & \alpha_1 Win_{ij} \times Exp_{ij} + \alpha_2 Loss_{ij} \times Exp_{ij} + \\ & \alpha_3 Win_{ij} \times Une_{ij} + \alpha_4 Tie_{ij} + \alpha_5 Loss_{ij} \times Une_{ij} + \varepsilon_{ij}. \end{aligned} \tag{4}$$

In this model, $\alpha_1$ and $\alpha_2$ measure the average abnormal returns following expected wins and losses, while $\alpha_3$, $\alpha_4$ and $\alpha_5$ measure the average abnormal returns following unexpected wins, ties and losses. It is worth noting that, as already pointed out, all the ties in our data set are unexpected, thus it is not possible to identify the average abnormal return following expected ties. Our hypothesis can be stated as follows:

- $H_7$: $\alpha_3 > \alpha_1 \geq 0$, $\alpha_5 < \alpha_2 \leq 0$, and $\alpha_4 \cong 0$.

We expect larger abnormal returns following unexpected events, that is, unexpected wins and losses should determine larger abnormal returns than expected wins and losses respectively. More specifically, if the pre-match betting odds fully reflected all available information on the most likely match score, $\alpha_1$ and $\alpha_2$ should (coherently with the efficient market hypothesis) both be equal to 0. If, on the other side, the pre-match betting odds only partially reflected available information on the most likely match score or the mood effect were particularly strong, $\alpha_1$ and $\alpha_2$ could differ from 0.

[11] Soccer leagues across Europe start and end at different times. Thus, including dummies for every month may not be the best way to detect the presence of seasonality in our data. Therefore, results of this test should be interpreted with caution.

# 4 Event study results

In this section, we present the results of our event-study analysis. The following subsections are devoted to testing the hypotheses stated in the previous section.

## 4.1 Market reaction to match results, goal difference, and site of competition

The first hypothesis we test is $H_1$. The results of the estimation of Eq. (1) are presented in Table 2, which shows statistically significant positive market reactions following wins (0.792 per cent) and negative ones following losses (–1.142 per cent). Furthermore, the average abnormal return following losses is larger in absolute terms than the average abnormal return following wins. All these results are in line with expectations (and with previous findings in the literature). However, we reject the hypothesis of no market reaction associated with ties: ties seem to have a negative effect in terms of abnormal returns, even if their effect is not as large as the one associated with losses (–0.371 per cent). Thus, our results shed new light on the informational content of ties: investors seem to consider ties as negative rather than neutral events. This result could be explained considering that ties reduce the probability of winning a championship or a cup, and that all soccer teams in our sample are upper-tier teams in their respective leagues.

**Table 2** Match result and abnormal returns

| Variable | Estimate | Std. error | p-value | Sign. |
|---|---|---|---|---|
| *Loss* | –1.142 | 0.169 | < 0.001 | *** |
| *Tie* | –0.371 | 0.175 | 0.034 | ** |
| *Win* | 0.792 | 0.138 | < 0.001 | *** |

***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Once we have verified that abnormal returns are affected by match results, we test the second hypothesis ($H_2$) by estimating Eq. (2). Indeed, the results (see Table 3) seem to support our hypothesis: abnormal returns increase with goal difference. Furthermore, as expected, the positive effect of goal difference is nonlinear and increases less than proportionally for larger goal differences.

**Table 3** Delta score and abnormal returns

| Variable | Estimate | Std. error | p-value | Sign. |
|---|---|---|---|---|
| *Intercept* | –0.088 | 0.105 | 0.400 | – |
| *Delta* | 0.457 | 0.056 | < 0.001 | *** |
| Squared *Delta* | –0.042 | 0.016 | 0.008 | *** |

***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

The results of this second model are consistent with those of the first model: match results affect abnormal returns, and this effect increases less than proportionally by the intensity of the result. This nonlinear pattern (depicted in Fig. 1) can be interpreted as follows: the positive coefficient on the linear term (0.457 per cent) identifies win- or loss-related moods (e.g., winning is preferable to tying or losing); the negative coefficient on the quadratic term (–0.042 per cent) may imply satiety (a greater overall goal difference at the end of a league rarely gives a significant advantage) or a disparity in the strength of the two teams, which thus reduces the importance of the win itself.

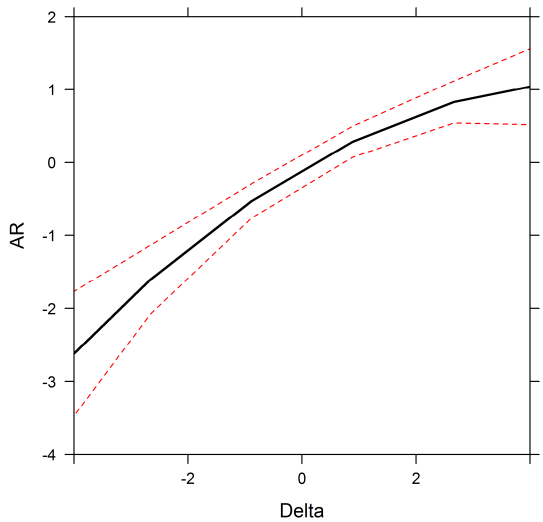


**Fig. 1** Non linearity in delta score along with 95 per cent confidence interval around the estimated effect

We now test our third hypothesis ($H_3$), regarding to effects of home and away matches, for which results are presented in Table 4. First, we note that the estimated coefficients of Model (3) are in line with those presented in Table 2: a positive market reaction follows wins (1.021 per cent at home and 0.476 per cent away), a negative market reaction follows losses (–1.317 per cent at home and –1.045 per cent away), and a negative market reaction is suggested for ties (a non-significant coefficient for home ties and a weakly significant –0.437% for away ties). Second, we test whether the location where a match is played (at home or away) influences abnormal returns. A joint Wald test, based on a reparameterization of the model – not reported for brevity – shows that there is no statistically significant difference between the abnormal returns of matches played at home or away (Wald test = 1.514, p-value = 0.209). Thus, the presence of a site of competition effect is not supported by the data. This evidence is not consistent with the stylized fact that playing at home is an important advantage for a soccer team and leads to a rejection of $H_3$.

**Table 4** Site of competition and abnormal returns

| Variable | Estimate | Std. error | p-value | Sign. |
|---|---|---|---|---|
| *Loss Away* | –1.045 | 0.211 | < 0.001 | *** |
| *Tie Away* | –0.437 | 0.248 | 0.078 | * |
| *Win Away* | 0.476 | 0.215 | 0.027 | ** |
| *Loss Home* | –1.317 | 0.281 | < 0.001 | *** |
| *Tie Home* | –0.300 | 0.245 | 0.221 | – |
| *Win Home* | 1.021 | 0.179 | < 0.001 | *** |

***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

## 4.2 Competition type and date effect

In this section, we test our hypotheses regarding the competition type and date. The first hypothesis ($H_4$) concerns the influence of the type of competition on abnormal returns. We estimate a model distinguishing among different competition types (i.e., national championship, Champions League, UEFA Cup, other international cups, and national cup matches), and we find a strongly statistical difference in abnormal returns associated with different types of competition (Wald test = 4.0529, p-value < 0.000). Instead of reporting the results in a table (showing 15 coefficients), we prefer to plot the regression coefficients in a figure (see Fig. 2). The abnormal returns registered for the national championship are fully consistent with those reported in Model (1): wins elicit positive abnormal returns; ties and losses are associated with negative abnormal returns. The same finding applies to Champions League and national cup matches, even if with differences in the magnitude of abnormal returns. For UEFA Cup wins (negative abnormal returns) and international cup losses and ties (positive abnormal returns), we find non-significant coefficients, thus no abnormal returns are detected in these cases. This statistical insignificance may be justified by the small number of observations for these competition types. However, all in all, the empirical evidence seems to support our hypothesis ($H_4$) that different types of competition are not equally important.

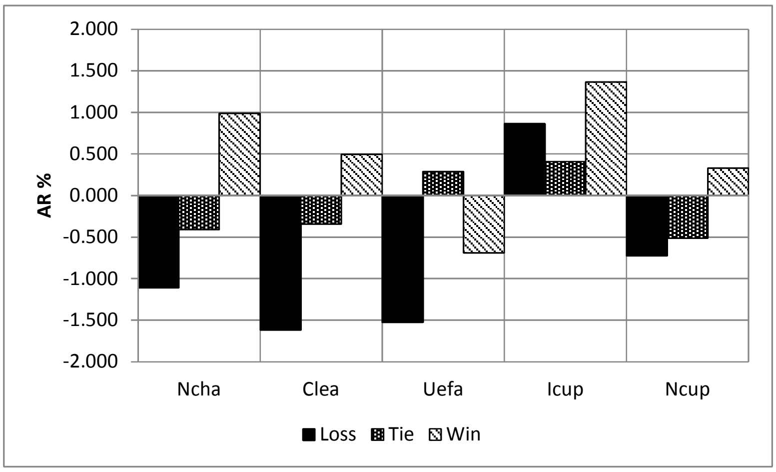


**Fig. 2** Competition type and abnormal returns

The fifth hypothesis ($H_5$) focuses on the year of competition (2007, 2008 and 2009). We hypothesized potential differences in the abnormal returns associated with these three years. Fig. 3 seems to support this hypothesis. However, a joint Wald test on the year effect rejects the hypothesis of changing abnormal returns over the years considered (Wald test = 1.647, p-value = 0.130). Thus, $H_5$ is not supported by our data.

Finally, we test for the presence of a month effect ($H_6$). Fig. 4 shows that the abnormal returns in different months mimic those of Model (1) (with few exceptions). Furthermore, the figure seems to suggest that the month in which the match takes place influences the magnitude of the abnormal returns. A joint Wald test on the month effect supports this hypothesis (Wald test = 2.060, p-value = 0.000). The strongest reaction is registered at the end of season in July (despite the fact that abnormal returns in June are not significantly different from the average ones), supporting our hypothesis that the period of the year in which the match takes place affects the importance of the match itself. On the other hand, it is worth noting that only 14 matches in our data set were played in July.[12] Thus, caution is needed in interpreting this finding.

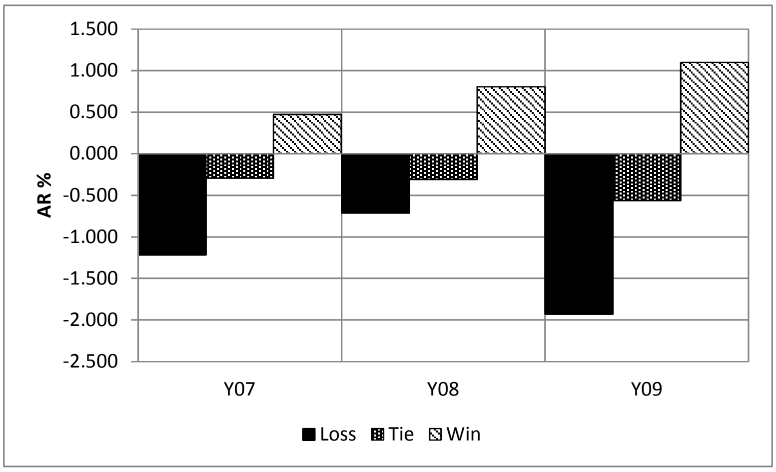


**Fig. 3** Year of competition and abnormal returns

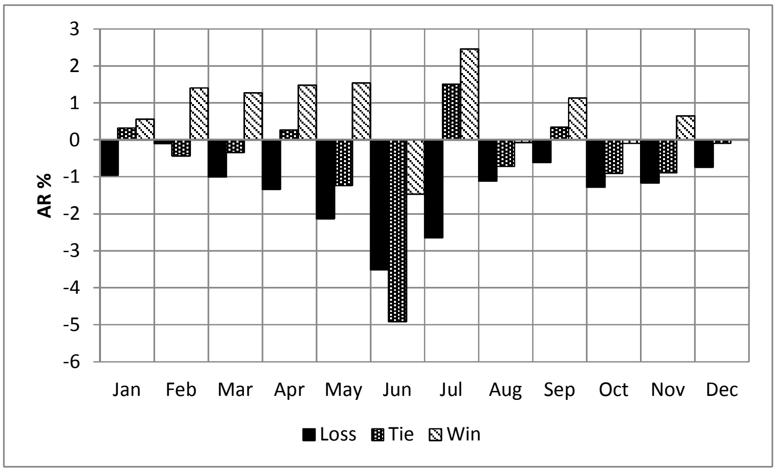


**Fig. 4** Month of competition and abnormal returns

[12] Most championships have already ended by July. See also footnote 7.

### 4.3 Informational value of bets

In this section, we focus on our seventh hypothesis ($H_7$), that is, that unexpected results produce greater abnormal returns – in absolute value – than the expected ones. To test this hypothesis, we estimate Model (3) and present the results in Table 5. The abnormal returns associated with wins and losses follow the same pattern seen above, for both expected and unexpected events. Furthermore, unexpected ties (the only available) register negative abnormal returns. All these results are in line with those of Model (1). Focusing more in depth on $H_7$, a joint Wald test does not reject the null of no effect of unexpected events (Wald test = 0.2255, p-value = 0.7981). Thus, according to these results, we reject $H_{7,}$ which predicts a stronger market reaction following unexpected events. Since this result is counterintuitive, it needs to be analysed further.

**Table 5** Informational value of bets

| Variable | Estimate | Std. Error | p-value | Sign. |
|---|---|---|---|---|
| *Exp Loss* | –1.028 | 0.266 | < 0.001 | *** |
| *Exp Win* | 0.808 | 0.139 | < 0.001 | *** |
| *Une Loss* | –1.244 | 0.250 | < 0.001 | *** |
| *Tie* | –0.371 | 0.188 | 0.048 | ** |
| *Une Win* | 0.685 | 0.359 | 0.057 | * |

***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

## 5 The problem of overlapping events: an SUR approach

A problem with the standard event-study methodology is that it generally deals with non-overlapping events. In case of non-overlapping events, it is reasonable to assume abnormal returns on individual securities to be uncorrelated between teams (one of the main hypotheses in event-study testing procedures). However, most matches are played in the same days, thus the non-overlapping hypothesis does not hold. Ignoring event date clustering could result in biased standard errors, which in turn may lead to misleading results in hypothesis testing.

In our dataset, the average number of events per day is around 12. Thus, the problem of overlapping events is a concern. To accommodate this potential problem, we apply an SUR model (Zellner 1962) to retest $H_1$ and $H_7$. The SUR model specification takes into account the crossectional correlation due to the clustering of event days, allowing the covariances between the abnormal returns to be non-null (Schipper and Thompson 1985). We focus only hypotheses $H_1$ and $H_7$ because, by construction, the SUR model does not allow to retest the remaining ones. To do so, our data set should include observations for each possible combination of variables (e.g., wins and losses for each team and for each month).

Formally, the SUR model can be seen as a generalization of a standard linear regression model consisting of several regression equations. For each team $i$, let $\mathbf{r}_i$ denote a $T \times 1$ vector of daily returns, with generic element $r_{it}$ ($t = 1,\ldots,T$), $\mathbf{X}_i$ a $T \times k$ matrix of $k$ covariates, $\boldsymbol{\varepsilon}_i$ a $T \times 1$ vector of error terms and $\boldsymbol{\beta}_i$ a $k \times 1$ vector of regression coefficients.[13] Then, the SUR model consists of $N$ equations (one for each soccer team) of the form

$$\mathbf{r}_i = \mathbf{X}_i \boldsymbol{\beta}_i + \boldsymbol{\varepsilon}_i, \; i = 1, \ldots, N. \tag{5}$$

Two main assumptions on the errors of an SUR model are:

$$E\left(\boldsymbol{\varepsilon}_i \mid \mathbf{X}_1, \ldots, \mathbf{X}_N\right) = \mathbf{0}, \; i = 1, \ldots, N; \text{ and}$$

$$\mathrm{Cov}\left(\boldsymbol{\varepsilon}_i, \boldsymbol{\varepsilon}_j \mid \mathbf{X}_1, \ldots, \mathbf{X}_N\right) = \begin{cases} \sigma_i^2 \mathbf{I}_T & \text{if } i = j \\ \sigma_{ij} \mathbf{I}_T & \text{if } i \neq j \end{cases},$$

where $\mathbf{I}_T$ is a $T \times T$ identity matrix.

It is important to note that the system in Eq. (5) does not provide a structural relationship among the different equations (i.e., the dependent variable of one equation never appears among the covariates of other equations). However, it is clear from the covariance equation above that the $N$ equations are linked through the error covariances $\sigma_{ij}$. This assumption is crucial because it allows

[13] It should be noted that, for SUR estimation purposes, the variables described in Table 1 are restructured by allowing for as many time periods as the number of trading days in the period 2007–09.

the correlation across the abnormal returns of different teams to assume any values and implies unobserved variables with correlated values between equations.

An SUR model can be estimated by means of the feasible generalized least squares (FGLS) method. As $T$ diverges, the FGLS estimator is consistent, efficient and normally distributed.[14]

After presenting the main methodological features of SUR, we now focus on retesting $H_1$. To do so, we estimate an SUR model in which each equation (one per team) can be formalized as

$$r_{it} = \alpha_i + \beta_i^W Win_{it} + \beta_i^T Tie_{it} + \beta_i^L Loss_{it} + \mathbf{con}'_t \boldsymbol{\gamma}_i + \varepsilon_{it}, \tag{6}$$

where: $Win_{it}$, $Tie_{it}$ and $Loss_{it}$ are dummy variables indicating if the soccer team $i$ won, tied, or lost a match at time $t$; $\beta_i^W$, $\beta_i^T$ and $\beta_i^L$ measure the market reaction following wins, ties and losses, respectively; $\boldsymbol{\gamma}_i$ is the vector of coefficients associated with the control variables included in $\mathbf{con}_t$.[15] In particular, we estimate three models, which differ for the control variables included in $\mathbf{con}_t$. In the first one, we do not include any control (i.e., we impose $\boldsymbol{\gamma}_i = \mathbf{0}, \forall i$). In this model, $\alpha_i$ measures the average return that occurs when no matches are played, and the abnormal returns are defined as a deviation from $\alpha_i$ when matches are instead played. In the second model, to take into account the systematic component of stock returns, we add the variable $Mkt_t$ among the controls.[16] $Mkt_t$ is the STOXX® Europe 600 index's logarithmic daily return, used as a proxy for market return. Finally, in the third model, we consider a possible year effect by adding year dummies among the control variables.

[14] The model can alternatively be estimated equation-by-equation using ordinary least squares (OLS). Even if the OLS estimator is consistent, it is not efficient because it ignores the cross-correlation between errors.

[15] It is worth noting that the control variables are the same for each equation, thus we do not need the team-specific index $i$ to characterize the vector $\mathbf{con}_t$.

[16] More sophisticated models can be used to analyse abnormal returns (e.g., the Fama-French three- factor model, or Carhart's four-factor model; see Fama and French 1993; Carhart 1997). However, previous literature on short-term event studies (Campbell et al. 1997) points out that empirical results are virtually unaffected by the choice of the model. This is especially true in our case: the three additional factors employed in the four-factor model (size, value and momentum) play a negligible role here, as the stocks considered belong to the same sector and are quite homogeneous.

After estimating our SUR models, we test the joint significance of all the coefficients $\beta_i^W$, $\beta_i^T$ and $\beta_i^L$ (one for each team *i*) by means of three tests: Wald test (F-distributed), Wald test and Likelihood ratio tests (both Chi-squared-distributed).[17]

Since for each team we estimate a different set of coefficients $\beta_i^W$, $\beta_i^T$ and $\beta_i^L$, as a summary measure we report average values by type of coefficient:

$$Ar^W = \frac{1}{23}\sum_{i=1}^{23}\beta_i^W; \;\; Ar^T = \frac{1}{23}\sum_{i=1}^{23}\beta_i^T; \;\; Ar^L = \frac{1}{23}\sum_{i=1}^{23}\beta_i^L, \qquad (7)$$

where $Ar^W$, $Ar^T$ and $Ar^L$ are the average abnormal returns following wins, ties and losses, respectively.

Focusing on $H_7$, we estimate a further SUR model in which each equation is written as

$$\begin{aligned} r_{it} = \alpha_i + \beta_i^W Win_{it} + \beta_i^T Tie_{it} + \beta_i^L Loss_{it} + \\ \delta_i^W \left(Une_{it} \times Win_{it}\right) + \delta_i^L \left(Une_{it} \times Loss_{it}\right) + \mathbf{con}'_t \boldsymbol{\gamma}_i + \varepsilon_{it}. \end{aligned} \qquad (8)$$

In Eq. (8), $Win_{it}$, $Tie_{it}$ and $Loss_{it}$ indicate, as in Eq. (6), if the soccer team *i* won, tied, or lost a match at time *t*, while $Une_{it}$ is a dummy variable indicating if the match result was unexpected based on the information of the pre-match betting odds. Based on this model specification, $\beta_i^W$ and $\beta_i^L$ measure the market reaction following expected wins and losses, respectively, while similarly, $\delta_i^W$ and $\delta_i^L$ measure the difference in abnormal returns when the same events were unexpected. Thus, $\beta_i^W + \delta_i^W$ and $\beta_i^L + \delta_i^L$ indicate the total abnormal returns associated with unexpected wins and losses, respectively. $\beta_i^T$ represents the abnormal return associated with unexpected ties. Once more, $\boldsymbol{\gamma}_i$ is the vector of coefficients associated with the control variables included in $\mathbf{con}_i$.

Similarly to what was done for $H_1$, we test the joint significance of all the above coefficients, and report the average value of all coefficient types as a summary statistic:

[17] While the latter two, which are asymptotically equivalent, are especially indicated for large samples, the former has better finite sample properties.

$$Ar^{W} = \frac{1}{23}\sum_{i=1}^{23}\beta_i^{W};\ Ar^{T} = \frac{1}{23}\sum_{i=1}^{23}\beta_i^{T};\ Ar^{L} = \frac{1}{23}\sum_{i=1}^{23}\beta_i^{L};$$
$$\Delta UneAr^{W} = \frac{1}{23}\sum_{i=1}^{23}\delta_i^{W};\ \Delta UneAr^{L} = \frac{1}{23}\sum_{i=1}^{23}\delta_i^{L}, \tag{9}$$

where $Ar^W$, $Ar^T$ and $Ar^L$ are the average abnormal returns following expected wins, ties, and expected losses, respectively, while $\Delta UneAr^W$ and $\Delta UneAr^L$ measure the average abnormal returns differential for unexpected wins and losses.

## 5.1 Reassessment of market reaction

We first retest $H_1$. To do so, we estimate three SUR models, which differ according to the control variables included (indicated in the bottom of Table 6). While the first model includes no control variables, the second and the third models introduce among the controls the market returns and year dummy variables. It is worth noting that the results of the three models agree in the sign and magnitude of the average coefficients reported.

**Table 6** Average market reaction to match results

| Abnormal return (AR percent) | | | |
|---|---|---|---|
| | SUR 1 | SUR 2 | SUR 3 |
| $Ar^W$ | 0.589 | 0.627 | 0.631 |
| Wald test (F-test) | 3.914*** | 4.230*** | 4.258*** |
| Wald test (Chi-squared-test) | 90.030*** | 97.286*** | 97.925*** |
| Likelihood ratio test (Chi-squared-test) | 86.280*** | 93.060*** | 93.836*** |
| $Ar^T$ | –0.687 | –0.626 | –0.631 |
| Wald test (F-test) | 2.410*** | 2.262*** | 2.246*** |
| Wald test (Chi-squared-test) | 55.430*** | 52.034*** | 51.649*** |
| Likelihood ratio test (Chi-squared-test) | 54.155*** | 50.946*** | 50.767*** |
| $Ar^L$ | –1.476 | –1.451 | –1.443 |
| Wald test (F-test) | 6.126*** | 6.165*** | 6.106*** |
| Wald test (Chi-squared-test) | 140.900*** | 141.800*** | 140.430*** |
| Likelihood ratio test (Chi-squared-test) | 137.200*** | 138.110*** | 137.240*** |
| **con**$_t$ | | | |
| $Mkt^t$ | No | Yes | Yes |
| Year dummies | No | No | Yes |

***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Table 6 presents the values of $Ar^W$, $Ar^T$ and $Ar^L$ as defined above. Consistently with Sect. 4.1, our results show a statistically significant positive market reaction following wins, and a statistically significant negative market reaction following ties and losses. The average abnormal return following losses is larger in absolute terms than the average abnormal return following wins. In addition, ties appear to have a negative effect, even if their effect is not as large as the one associated with losses.

We now retest $H_7$. Table 7 reports the estimation of our three SUR models, which agree in sign and magnitude of the average estimated coefficients: $Ar^W$, $Ar^T$, $Ar^L$, $\Delta UneAr^W$ and $\Delta UneAr^L$.

Our results show a statistically significant positive (negative) market reaction following expected wins (losses). Once again, the absolute average abnormal return following losses is larger than the one following wins, and ties seem to have a negative effect. These results agree with the findings of Sect. 4.3. However, when looking at $\Delta UneAr^W$ and $\Delta UneAr^L$, we observe that unexpected events generate a larger market reaction than expected event. In particular, in all three models, $\Delta UneAr^W$ is positive and $\Delta UneAr^L$ is negative. Thus, on average, unexpected events are associated with larger abnormal returns. This result is consistent with $H_7$ and contrasts with our findings in Sect. 4.3, suggesting that not accounting for overlapping events may lead to unreliable inference.

## 5.2 The distribution of individual abnormal returns

Since in the previous section we find that the SUR model leads to different findings with respect to the standard event-study approach for $H_7$, it is worth inspecting the entire distribution of individual abnormal returns. In order to analyse the potential heterogeneity of the individual coefficients[18] $Ar^W$, $Ar^L$, $Ar^W + \Delta UneAr^W$, $Ar^T$ and $Ar^L + \Delta UneAr^L$, in Fig. 5 we report five boxplots. Boxplots show the distribution of abnormal returns conditionally to expected and unexpected match results.

[18] We use the coefficients estimated for the third SUR model (SUR 6, which controls for the market and year effects), but our conclusions are virtually unaffected by this choice.

The extremes of the box correspond to the first and third quartiles ($Q_1$ and $Q_3$). The vertical height of the box represents the inter-quartile difference $(\delta_Q = Q_3 - Q_1)$, a measure of variability. The horizontal bold line inside each box represents the median, while the black point is the average. Finally, the lower and upper external lines correspond to $Q_1 - 1.5\delta_Q$ and $Q_3 + 1.5\delta_Q$, respectively. Observations beyond these lines indicate the presence of outliers. While the preceding analysis was limited to providing the average abnormal return related to match results (a measure of central tendency), the boxplots are more informative.

The plots of the first column of Fig. 5 present the abnormal returns in case of expected and unexpected wins, respectively. Coherently with our results in the previous section, the average (and median) abnormal return in the two plots is positive with a larger abnormal return for unexpected wins. Furthermore, the two plots show that the main part of the distribution of individual teams' abnormal returns is characterized by positive abnormal returns. The second plot of the second column of Fig. 5 presents the abnormal returns in case of (unexpected) ties. In this case, the average (and median) abnormal return is negative, but the distribution appears to be asymmetric: the median is close to the upper extreme of the box. Finally, the plots of the third column of Fig. 5 present the abnormal returns in case of expected and unexpected losses. In this case, the negative market reaction following this event is evident: the average (and median) abnormal return is strongly negative in both plots (with a larger abnormal return in case of unexpected losses) and all the abnormal returns appear to be concentrated in the negative quadrant of the plot around the median.[19] Thus, the SUR model results appear to be largely confirmed when inspecting the distribution of the team-specific coefficients.

[19] The only exception is a positive (non-significant) abnormal return associated to Futebol Clube Do Porto.

**Table 7** Average market reaction to expected and unexpected results

| Abnormal return (AR percent) | | | |
|---|---|---|---|
| | SUR 4 | SUR 5 | SUR 6 |
| $Ar^W$ | 0.509 | 0.550 | 0.553 |
| Wald test (F-test) | 3.621*** | 3.9169*** | 3.941*** |
| Wald test (Chi-squared-test) | 83.272*** | 90.088*** | 90.642*** |
| Likelihood ratio test (Chi-squared-test) | 80.352*** | 86.724*** | 87.435*** |
| $Ar^T$ | –0.702 | –0.637 | –0.641 |
| Wald test (F-test) | 2.491*** | 2.323*** | 2.301*** |
| Wald test (Chi-squared-test) | 57.288*** | 53.421*** | 52.929*** |
| Likelihood ratio test (Chi-squared-test) | 56.305*** | 52.657*** | 52.388*** |
| $Ar^L$ | –1.158 | –1.169 | –1.166 |
| Wald test (F-test) | 3.012*** | 2.924*** | 2.934*** |
| Wald test (Chi-squared-test) | 69.272*** | 67.243*** | 67.478*** |
| Likelihood ratio test (Chi-squared-test) | 67.177*** | 65.091*** | 65.493*** |
| $\Delta UneAr^W$ | 0.493 | 0.492 | 0.494 |
| Wald test (F-test) | 1.572** | 1.726** | 1.704** |
| Wald test (Chi-squared-test) | 36.153** | 39.686** | 39.183** |
| Likelihood ratio test (Chi-squared-test) | 35.090** | 38.505** | 38.152** |
| $\Delta UneAr^L$ | –0.639 | –0.596 | –0.591 |
| Wald test (F-test) | 2.348*** | 2.133*** | 2.137*** |
| Wald test (Chi-squared-test) | 53.998*** | 49.050*** | 49.141*** |
| Likelihood ratio test (Chi-squared-test) | 52.455*** | 47.765*** | 47.979*** |
| $\mathbf{con}_t$ | | | |
| $Mkt_t$ | No | Yes | Yes |
| Year dummies | No | No | Yes |

***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

## 6 Conclusions

Several studies suggest that match results influence investor mood, which in turn affects sport teams stock returns. Wins are generally associated with a good mood and losses with a bad mood. These emotional reactions affect investor behavior on the market, which reacts positively to wins and negatively to losses.

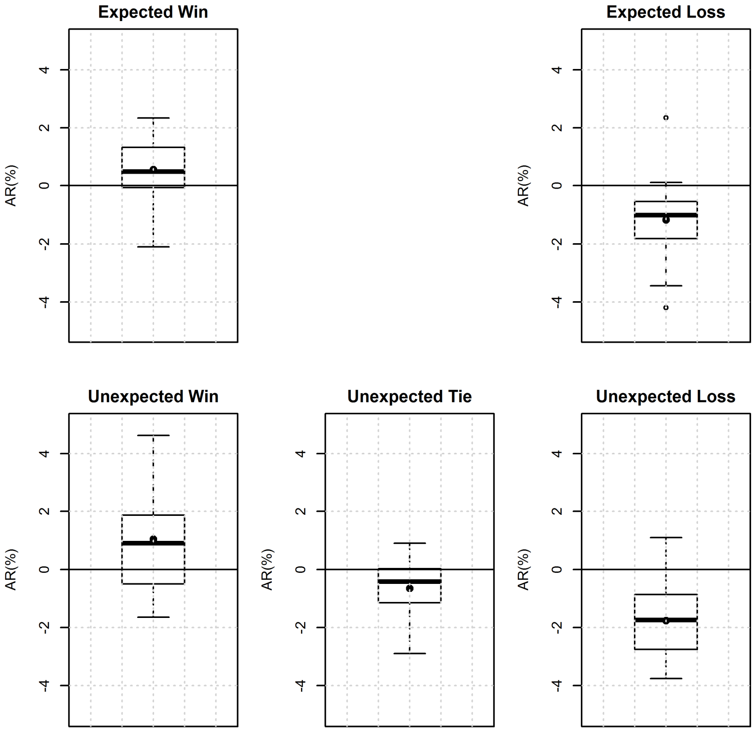


**Fig. 5** Distribution of individual abnormal returns among soccer teams

In this work, we analyse the relationship between soccer match results, bets and stock returns of all listed European soccer teams. Our data set includes all national and international match results and pre-match betting odds for all 23 listed European soccer teams, in the period between 2007 and 2009. To measure the aggregate market reaction to match results, we use an event-study approach. Our main results can be summarized as follows:

i. While wins are followed by positive abnormal returns, ties and losses are followed by negative abnormal returns. Furthermore, abnormal returns following losses are larger in magnitude than those following wins. Positive and negative abnormal returns are nonlinearly related to the intensity of a match result, as measured by goal difference.

ii. On the one hand, abnormal returns are affected by both the type and the month of competition; on the other hand, the location where the match is played (home vs away) or the year of competition do not appear to influence abnormal returns.

iii. When we use an SUR model specification to accommodate the problem of event clustering, positive and negative abnormal returns are magnified by unexpected match results. In particular, the latter result represents the main contribution of this paper to the existing literature on event studies.

The objective of this paper was not to identify a profitable trading strategy. However, albeit indirectly, our results suggest some trading rules that may be applied by investors. For example, investors may choose to rebalance their personal portfolios by buying stocks of the teams that are expected to win, and by selling those of the teams that are expected to lose. Future extensions of this paper could attempt to measure the expected profit of this investment strategy. Furthermore, since positive and negative abnormal returns are magnified by goal difference, future research could explore the relationship between the pre-match betting odds on the number of goals scored and the actual goal difference.

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**Appendix A** List of teams

| Club | Country | Number of matches | Market value 2009 (mln) | Beta |
|---|---|---|---|---|
| Celtic | Great Britain | 105 | 34.13 | 0.29 |
| Borussia Dortmund | Germany | 79 | 156.08 | 0.95 |
| Tottenham Hotspur | Great Britain | 109 | 83.64 | 0.48 |
| Afc Ajax | Netherlands | 91 | 113.12 | 0.39 |
| Lazio | Italy | 97 | 32.30 | 0.45 |
| Brondby If B | Denmark | 85 | 73.50 | 0.68 |
| Arhus Elite | Denmark | 76 | 74.94 | 0.67 |
| Sport Lisboa E Benfica | Portugal | 86 | 10.35 | 0.54 |
| Silkeborg | Denmark | 62 | 64.24 | 0.56 |
| Futebol Clube Do Porto | Portugal | 91 | 3.15 | 0.43 |
| Watford | Great Britain | 105 | 0.55 | 0.61 |
| Galatasaray | Turkey | 104 | 538.10 | 0.64 |
| Aalborg Boldspilklub | Denmark | 100 | 25.48 | 0.79 |
| Millwall Hldg | Great Britain | 107 | 2.43 | 0.32 |
| Sporting | Portugal | 86 | 0.06 | 0.25 |
| Aik Football | Sweden | 89 | 30.45 | 0.18 |
| Parken Sport & Entertainment | Denmark | 99 | 846.64 | 0.84 |
| Trabzonspor Sportif Yatir | Turkey | 80 | 260.00 | 0.65 |
| Fenerbahce Sportif Hizmet | Turkey | 105 | 977.50 | 0.72 |
| Juventus | Italy | 97 | 212.44 | 0.64 |
| Besiktas | Turkey | 97 | 170.00 | 0.97 |
| As Roma | Italy | 103 | 67.06 | 0.77 |
| Olympique Lyonnais | France | 104 | 39.06 | 0.72 |