LISBON SCHOOL OF ECONOMICS & MANAGEMENT
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DISSERTATION

IS THE STOCK MARKET INFLUENCED BY THE RESULTS OF NATIONAL FOOTBALL TEAMS?

DIOGO GUILHERME CÂMARA CORREIA

OCTOBER - 2016

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ORIENTATION:

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Resumo

Este estudo analisa o efeito do humor dos investidores no mercado bolsista. Nos últimos anos muitos autores encontraram uma relação entre desporto e humor e, tendo por base essas descobertas, decidimos utilizar os resultados dos jogos das selecções nacionais de futebol como variável de humor. Concluímos que a média dos retornos diários após dias de jogo é inferior à que se verifica nos dias subsequentes a dias em que não foram disputados jogos e que as derrotas têm um impacto estatisticamente significativo nos retornos após dias de jogo.

Palavras-chave: futebol, mercado bolsista, retornos diários, finanças comportamentais.

Abstract

This study analyzes the effect of investors' mood in the stock market. In the past years many authors found a relationship between sports and mood and, motivated by those findings, in our study we use international football as a variable of mood. We conclude that the daily mean returns after game days are lower than the ones after no game days and that losses have a statistical significant impact in the returns that follows a game day.

Keywords: football, stock market, daily returns, behavioral finance.

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1 Introduction

Standard modern financial theory is based on the assumption that the representative economic agent is rational in two ways: his/her decisions are made according with axioms of the expected utility theory; and the ability of making unbiased forecasts about the future (Thaler (1999)).

Behavioral finance claims that economic agents are “normal” people, Statman (2014), and, therefore, they can make non rational decisions and their expectations towards the future might be biased.

Many authors credit these irrational decisions to investors’ mood or sentiment, and, more recently, a few of them tried to use the outcome of football games as a variable of mood, that influences positively (negatively) the investors’ mood if their team wins (loses), Edmans et al. (2007). These changes in investors’ sentiment may trigger different reactions towards the stock market, concerning the way investors perceive risk and their ability to do unbiased predictions.

Taking in consideration these recent studies, we intend to analyze the effect of the results of national football teams in the country’s stock index. This work will be divided in five different sections: section 2 contains a literature review; section 3 explains the data and methodology; section 4 exhibits the results and section 5 presents the conclusions.

2 Literature Review

Football is one of the most popular and played sports all over the world. The recent FIFA World Cup 2014, in Brazil, had a total in-home audience reach of more than two billion spectators[1], reaching an audience of 695 million viewers[2] in the final match against Germany and Argentina. Concerning the attendance in the stadiums, the World Cup 2014 had a total attendance of 3,429,873 spectators, averaging 53,592 spectators per match. This happens not only because of the popularity of the game or tournament, but also due to the stardom of its players. For example, elements such Cristiano Ronaldo reaches more than 100 million followers on Facebook.

Looking at these numbers, we can easily understand that football is present in the lives of a large number of people and, sometimes, football may incite other emotions than just the excitement of winning or the disappointment of losing. Archer (1976) cited the opinion of a Scottish supported after one of Scotland's international matches: *"For a time before, throughout and after I have the feeling that my personal worth is bound up with Scotland's success or failure"*.

Schwarz et al. (1987) studied the effect of the outcome of two games of Germany in the World Cup 1982 on people's perception of their global well-being, satisfaction about work and income and satisfaction related with national issues. The conclusion was that after a win, individuals were more satisfied with their well-being, work and income, and with national issues. However, after a tie, people's satisfaction regarding these issues decreased.

[1] Total in-home audience reach for more than 20 consecutive minutes.
[2] In-home audience reach for more than 20 consecutive minutes.

Commissioned by Hudson, Chandler (2006) made a report in which residents in England were inquired about their opinion on how the World Cup and other sport events could affect their workplace. The result was that 70% of the men and 62% of the women inquired said that the World Cup would have an impact in their working environment. Even those who claimed to not have any interest in football agreed with this impact.

Carroll et al. (2002) concluded that the admissions for heart attacks during a period of three days starting at June 30, 1998, increased by 25%. This period coincides with the loss of England against Argentina in a World Cup match, by penalty shoot-out.

Since football appears to have an impact in people's health and, more important, their opinion about personal and national issues, one could expect football to affect economic related issues as well, in particular the stock market. The idea might sound weird at the beginning, but it would not be the first time that a supposed economically neutral event has an impact in the financial markets: Kamstra, Kramer and Levi (2000) studied and found a relation between changes to and from daylight saving time with lower market returns; Saunders (1993) and Hirshleifer and Shumway (2003) found a link between the weather in the city of a country's largest stock exchange and low stock returns.

Concerning the effect of sports in people's mood, Wann et al. (1994) studied the reactions of undergraduate students after three games of the 1992-93 season of men's college basketball. The study concluded that after a win, spectators exhibit positive responses, however, after a loss, spectators responded with negative reactions.

Arkes et al. (1988) concluded that in the days after a win of the Ohio State University, the sales of the State of Ohio lottery tickets increased. This can represent that victories affect the way people perceive risk and/or the probabilities associated with certain events. Visceral factors (emotions such as anger or disappointment) have been proven to affect people's decision making under risk and uncertainty, and drives people to take impulse decisions, Loewenstein (1996, 2000).

If the outcomes of the games can affect the way investors perceive risk and probabilities of future returns, then it's expected that after a game investors might hold on to the wrong stocks. Shefrin and Statman (1985) and Odean (1998) studied the disposition effect – effect that shows a preference for selling "good" stocks and holding on to "bad" stocks. One explanation is that investors seek pride and try to avoid regret related to their investments, leading them to a greater disposition to realize gains than losses. Another explanation is that investors don't want to admit that their judgement was wrong, therefore holding on to these stock might give them time to turn a losing stock in a winning stock (especially if they overestimate the probabilities of returns).

Two factors that influence market prices are the risk-free rate and the equity risk premium. In his study, Abel (2002) demonstrates that pessimism and doubt can decrease the risk-free rate and increase the equity risk premium. Hence, both pessimism and doubt affect stock prices.

All these emotions described before, like overconfidence, happiness, pessimism or doubt, can be induced by a football game. A great win can boost the morale of investors and increase their willingness to invest. In the opposite direction, a defeat might turn out to be a big disappointment and make investors more pessimistic about their investments.

One of the first studies about the possible effects of football in the stock markets was Ashton et al. (2003). The study analyzes the effect of the games of England's national team in the FTSE100 index, during the time between the 6th of January 1984 and the 3rd of July 2002. In their study, they conclude that good (bad) performances of England's national team were followed by higher (lower) market returns. They also report that the effect in the stock market increases with the importance of the matches.

Six years later, Klein et al. (2009) wrote a critic review about the work of Ashton et al. (2003). The main criticisms were that Ashton et al. (2003) should have considered the holiday return effect, outliers and other events/news occurring at the same time as the games that could be economically relevant. Besides that, they also state that Ashton et al. (2003) should be more accurate concerning the day in which the game's outcome should be reflected in the market and found a mistake in one of the game's result used by Ashton et al. (2003). After exposing their criticism, Klein et al. (2009) made a replication of the Ashton et al. (2003) study, in which they did not find any link between England's national team performance and the FTSE100.

Ashton et al. (2011) responded to Klein et al. (2009) by redoing their previous work. In their new study they took in consideration some of the points stated by Klein et al. (2009) and also extended the period analyzed until the 10th of July of 2009. Once again, they concluded that there was a relationship between the England's national team performance and the FTSE100. They also concluded that the impact of wins and losses have been decreasing over time.

Berument et al. (2006a) studied the effect of the games of Besiktas, Fenerbahce and Galatasaray in the UEFA Winner's Cup on the Turkish stock market using a transfer function analysis. Analyzing the period between 1987 and 2003, they concluded that Besiktas' wins against foreign rivals increased the stock market returns, and that the wins of Fenerbahce and Galatasaray were not statistically significant. They also didn't found any statistical evidence of the effect of losses or draws in the stock market, mainly because Turkish supporters do not expect their teams to win against foreign rivals.

In another study of Berument et al. (2006b), it was shown that Besiktas' wins in European competitions increased industrial production in Turkey. In monthly terms, the growth rate of the industrial production associated with Besiktas' home and away-wins is 0.14% and 0.39% respectively.

Edmans et al. (2007) analyzed the effect of football, international cricket, ice hockey, rugby and basketball in the stock market, for 39 countries from January 1973 to December 2004. Regarding football, they studied events such as the World Cup, European Cup, Copa America and Asian Cup. They found a positive, but not statistically significant impact of wins and a strong negative reaction to losses (excess returns associated with losses exceed 7% in a monthly basis). They found these effects to be more pronounced in small stock, which are more sensitive to investor's sentiment. They also state that the effect in the stock market varies according with the importance of the game, which is also stated by Ashton et al. (2011). Considering the other sports, they also verified a statistically significant loss effect. However, this effect was smaller for these sports than for football.

Pantzalis and Park (2014) also studied the effect of other sports in the stock markets. In their analysis, they used the result of the four major leagues in the United States (NBA, NFL, NHL and MLB) between the sporting seasons of 1967/68 and 2007/08. They used three different stock exchanges (NYSE, NASDAQ and AMEX) and firms located within 100 miles radius from the city center of any of the professional teams in the previously mentioned leagues. They concluded that all the sports studied generated a sentiment that is strongly and positively correlated with the performance of the local firms' stocks. This finding is in accordance with Hirshleifer (2001), which states that investors are biased to buy stock from companies based in their home country. They also found that the initial mispricing of the stocks can be attributed to sports sentiment and that the price correction occurs slowly; that local trading behavior is affected by sports sentiment; that due to the increase of media coverage in the recent years, sport sentiment is now more pronounced; and that investment strategies based on sport sentiment could generate abnormal returns within a range from 0.08% to 0.13% per week.

Boyle and Walter (2003) studied the effect of rugby in the New Zealand's stock exchange between January 1950 and December 1999. However they didn't find any link between the All Blacks' success and the stock market returns.

Bernile and Lyandres (2011) analyzed the impact of football outcome in the club's own stock. The study was based in matches of the Champions League and UEFA Cup between the 2000/01 and 2005/06 seasons. In order to assess the probability of a certain game outcome, the authors used bookmakers' odds, since they are generally consistent and unbiased predictors of the game's outcomes. They found that the market reaction to football games is asymmetric, in the sense that losses are associated with significantly negative returns, and wins with near zero returns. Since investors in football clubs are usually overconfident about their team success before the games, this asymmetry can be explained by the lack of ability by investors to form unbiased ex ante beliefs.

In a similar study, Castellani et al. (2013) used bookmakers' odds to assess the reaction of the market concerning unexpected results. The authors found a statistically significant positive (negative) reaction following wins (losses). They also concluded that: average abnormal returns following losses are, in absolute terms, larger than average abnormal returns following wins; draws have a negative effect in abnormal returns, but not as large as the effect associated with losses; abnormal returns increase with goal difference; the difference between abnormal returns of matches played at home or away is not statistically significant; different competitions have different levels of importance, with the most important ones being the national league and the Champions League; there are evidence of the existence of a month effect, with the strongest reaction occurring during the month of July, near the end of football season; and that positive and negative abnormal returns are magnified by the existence of unexpected results.

Boido and Fasano (2007) also studied the effect of football clubs' performance in the clubs' stocks. They analyzed three Italian teams (Lazio, Juventus and Roma) during the period of January 2005 until June 2006. The conclusions were that price/return ratio following wins is higher than the one following losses, and that sport performance affects the financial performance of listed clubs.

In terms of profit seeking strategies, Kaplanski and Levy (2008) studied the effect of the World Cup in US market. They analyzed the period between January 1950 and December 2007 and concluded that the average return of the US market during World Cup days is -2.58%, compared to an average of 1.21% for all the other days over the same period. After checking the results for outliers, world events and a possible June-July seasonality, the authors concluded that the relation was robust and not spurious. Since this "World Cup Effect" in the US market is consistent over the years and does not depend on the outcome of the games, Kaplanski and Levy (2008) states that this anomaly can be exploited if an investor shorts the US market during the realization of the World Cup.

3 Data and Methodology

3.1 Data

For this study, it was collected the daily price of the stock market indices and the results of national football teams for ten different countries (South Korea, Japan, Argentina, Brazil, Netherlands, France, Germany, England, Spain and Portugal), between the period of January 1, 1993 and July 31, 2014.

These countries were selected due to their ranking and large number of titles and appearances in the four competitions analyzed in this study: FIFA World Cup, UEFA European Cup, CONMEBOL Copa America and AFC Asian Cup. In total, we have 51 titles won and 278 appearances divided by the ten countries chosen.

Regarding the FIFA World Ranking, we have 8 of the 10 teams selected in the top 20 (5 in top 10). South Korea and Japan are the lowest ranked nations of our sample, being ranked at number 50 and 53, respectively. Despite this, both teams have a major influence in their region, as we can see by their places in the top 3 of the Asian Football Confederation Ranking (South Korea appears as second and Japan as third).

This set of countries represents national teams that are more accustomed to winning than to losing, as we can see by the, approximately, 64% of wins in our sample. Since these teams are more used to winning, it is expected that when a loss occurs it will trigger a larger reaction. This fact will probably help us to assess the effect of loss aversion, which tells us that *"losses loom larger than gains"*, as said in Kahneman and Tversky (1979).

The period analyzed was chosen due to restrictions regarding the foundation of the stock index for each country. The Portuguese PSI-20 was the last index to be founded, in December 31, 1992; therefore, our analysis just starts in 1993. We could have used other indices that would allow us to enlarge our sample, however, in order to do a more consistent analysis, we decided to only use one index for each country.

This period also enables us to assess the effect of football results during different market trends, since it gathers together some moments of bull and bear markets, like the ones in the 90's and in the beginning of 2000, respectively.

The information regarding the stock markets was obtained from Datastream and it represents a total of 5630 daily observations for each country. Since the Brazilian price index was not available, it was used a total return index instead. For all the other countries we used the price index and then computed the log returns.

It was also collected data regarding the MSCI World Index, which includes large and middle capitalization companies from 23 developed countries.

Concerning the football data, friendly matches were excluded due to the lack of importance that most people attribute to these matches. Therefore, only official matches are taken into account, which give us a total of 1417 games (907 wins, 235 losses and 275 draws). The period analyzed comprises the qualification games and the final stages of six World Cups, five European Cups, seven Copa America and five Asian Cups. The results were obtained on www.rsssf.com and compared with the results available on the FIFA, UEFA and CONMEBOL websites.

In case a game is decided by a penalty shoot-out, the final result will be the same result verified at the end of the regular (or extra) time plus one goal to the team that wins the shoot-out. For example, the quarterfinal game between France and Netherlands in the 1996 European Cup ended with a 0-0 tie. In the penalty shoot-out, France won by 5-4. Therefore, in this study, the final result used is a 1-0 victory of France over Netherlands.

Some authors argue that unexpected results can provoke larger effects in the stock market. Most of these authors used betting odds to assess the expectancy of the game's outcome. Although betting odds are the best unbiased predictor that we can use, we could only find data starting at 2004, which excludes the first eleven years of our sample. Due to this problem, we also used Elo Ratings (ER) and then compare the results obtained. The Elo Rating System, created by Arpad Elo, is used by the international chess federation to rank chess players. In 1997, Bob Runyan adapted this system to international football. The betting odds were collected from http://www.oddsportal.com and the Elo Ratings are available at www.eloratings.net.

3.2 Methodology

This study will follow a similar approach to the one used in Edmans et al. (2007). However, we will introduce some new features to our analysis that we believe that can complement the previous study of Edmans et al. (2007). These differences allow us to explore more effects that can be triggered by different game scenarios, such as the expectancy of the game's outcome or the site of the game.

Since a common problem of stock market returns is its time-varying volatility, we started our approach by modeling a GARCH model to each country, in order to address this problem. Then, using the GARCH models, we computed the daily standard deviation in order to normalize the stock returns.

The normalized stock return allows us to eliminate heterogeneity between countries and is given by the following equation:

$$(1)\quad R_{it}^{n} = a_i + \frac{b_i \times R_{it}}{\sigma_{it}}$$

R^{n}_{it}, R_{it} and σ_{it} are the normalized returns, the returns and standard deviation for country i on day t, respectively. The values of a_i and b_i are chosen so that R^{n}_{it} has a mean equal to zero and a standard deviation equal to one. This procedure is the same one used in Edmans et al. (2007).

After computing the normalized returns, we used them to estimate the following model:

$$(2)\quad R_{it}^{n} = R_{it-1}^{n} + R_{t-1}^{MSCI} + R_{t+1}^{MSCI} + Monday_t + \varepsilon_{it}$$

As said previously, R^{n}_{it} is the normalized return for country i on day t. The previous return, R^{n}_{it-1}, is included to address the problem of serial correlation. The variable $Monday_t$ is a dummy variable that takes the value of 1 if day t is a Monday and zero otherwise, and is included to account for the Monday effect. Due to a possible correlation between stock markets of different countries, we decided to include the variables R^{MSCI}_{t-1} and R^{MSCI}_{t+1}. These variables represent the return on day $t-1$ and on day $t+1$ of the MSCI World Index. The return of the next day was also included to control for different time zones around the world.

We also estimated the equation with a dummy variable for each day of the week, in order to have a closer equation to the one used by Edmans et al. (2007). However, due to the absence of statistical significance of the other dummy variables, we decided to only include the variable Monday, which is the most traditional one.

It is important to state that, as Edmans et al. (2007), we also assumed that the effect of international football games would only occur in the next trading day available.

This assumption is made because the majority of games usually end when the stock markets are already closed.

Denoting $\widehat{\varepsilon_{it}}$ as the residuals of equation (2), we analyze the effect of international football results using the following regression:

$$(3)\ \hat{\varepsilon}_{it} = \beta_0 + \beta_W Win_{it-1} + \beta_L Loss_{it-1} + u_{it}$$

The variables Win_{it-1} and $Loss_{it-1}$ are two dummy variables representing wins and losses, respectively. Therefore, Win_{it-1} will take the value of 1 if country i wins a game on day $t-1$ and 0 otherwise; in the other hand, $Loss_{it-1}$ will take the value of 1 if country i loses a game on day $t-1$ and 0 otherwise.

This regression was first used with all the games available and, then, it was also used to evaluate the effect of the different stages of the tournaments (qualification, group and elimination games). These results can be found in Panel A of Table II.

Castellani et al. (2013) argue that the place where the game is played (home or away), the expectancy of the result (expected or unexpected) and the goal difference should trigger different reactions in the market.

To assess the difference between home and away games, we used the two following regressions:

$$(4)\ \hat{\varepsilon}_{it} = \beta_0 + \beta_W (Win_{it-1} \times Home_{it-1}) + \beta_L (Loss_{it-1} \times Home_{it-1}) + u_{it}$$

$$(5)\ \hat{\varepsilon}_{it} = \beta_0 + \beta_W (Win_{it-1} \times Away_{it-1}) + \beta_L (Loss_{it-1} \times Away_{it-1}) + u_{it}$$

The dummy variable $Home_{it-1}$ is classified as 1 if country i played a game in his own country on day $t-1$, and 0 otherwise. $Away_{it-1}$ is classified as 1 if country i played a game in a foreign country and 0 otherwise. The results for both these regressions are available in Table II, Panel B.

As said in the previous section, we used both betting odds and the Elo Ratting to assess if a game's outcome is expected or not.

Regarding the first hypothesis, after collecting the odds for the different games, we estimated the probabilities of the three different game outcomes as follows:

$$(6)\ P_{ij}^{WIN} = \frac{\frac{1}{O_{ij}^{WIN}}}{\frac{1}{O_{ij}^{WIN}} + \frac{1}{O_{ij}^{DRAW}} + \frac{1}{O_{ij}^{LOSS}}}$$

Where P^{WIN}_{ij} is the probability of country *i* winning game *j*; O^{WIN}_{ij}, O^{DRAW}_{ij} and O^{LOSS}_{ij} are the odds of country *i* winning, drawing and losing game *j*, respectively. The probabilities of losing and drawing are computed similarly.

After computing all the probabilities, it is assumed that the outcome with the highest probability is the expected one, and the others are unexpected. We then checked the results and compared them with the probabilities to make the variables $Expected_{it-1}$ and $Unexpected_{it-1}$. The variable $Expected_{it-1}$ is a dummy variable that assumes the value of 1 if country *i* obtains a result that is considered expected by the probabilities on day *t-1*. In a similar way, the variable $Unexpected_{it-1}$ will take the value of 1 if country *i* obtains a result that is considered unexpected by the probabilities on day *t-1*.

Regarding the Elo Ratings, to make the distinction between expected and unexpected outcomes, all games were first divided by three levels, taking in consideration the difference between the Elo Ratings:

- Level 1: $| ER_i – ER_j | \leq 70$: all results are considered expected;
- Level 2: $70 < | ER_i – ER_j | \leq 100$: a win by the team with the smallest Elo Rating is considered unexpected; a victory by the team with the highest Elo Rating or a draw is considered expected;

- Level 3: | ER_i – ER_j | > 100: a victory by the team with the smallest Elo Rating or a draw is considered unexpected; a victory by the team with the highest Elo Rating is considered expected.

Taking in consideration these three levels, it was then created two dummy variables, $Expected_{it-1}$ and $Unexpected_{it-1}$. The first takes the value of 1 if the result of country *i* on day *t-1* is expected and 0 otherwise. The second is defined analogously to the expected dummy variable.

With both dummy variables, of both methods, the following regressions were made:

$$(7)\ \hat{\varepsilon}_{it} = \beta_0 + \beta_W (Win_{it-1} \times Expected_{it-1}) + \beta_L (Loss_{it-1} \times Expected_{it-1}) + u_{it}$$

$$(8)\ \hat{\varepsilon}_{it} = \beta_0 + \beta_W (Win_{it-1} \times Unexpected_{it-1}) + \beta_L (Loss_{it-1} \times Unexpected_{it-1}) + u_{it}$$

The results for both regressions are displayed in Panel C and C2 of Table II.

Ashton et al. (2011) concluded that the impact of both wins and losses have been decreasing over time. In order to study such effect, we divided our sample period in three subsamples: 1993 to 1999, 2000 to 2007 and 2008 to 2014. Dividing our sample like this gives us the opportunity to look more carefully to three different periods. The first one, from 1993 to 1999, represents a fraction of time that is included in most of the studies that are referred in Section 2, and it goes until the burst of the dotcom bubble. The second subsample corresponds to the period of time when the first studies that tried to establish a relation between football and the stock market were published, including the study of Edmans et al. (2007), and it represents a period between the dotcom bubble and the financial crisis of 2008/09. This subsample also coincides with a period of time when the media started to give more importance to the broadcast of football games. The last subsample, from 2008 to 2014, allows us to study a period of time after the publication of several studies that analyzed the impact of football in the economy and also gives us the opportunity to look at the period after the financial crisis of 2008/09.

After dividing our sample in three subsamples, we then use these subsamples to run regression (3) again. Panel D of Table II illustrates the results.

To study the effect of goal difference we used the same regression as Castellani et al. (2013).

$$(9)\ \hat{\varepsilon}_{it} = \beta_0 + \beta_1 \times GoalDif_{it-1} + \beta_2 \times GoalDif_{it-1}^2 + u_{it}$$

The variable $GoalDif_{it-1}$ is defined as the goal difference in a game of country *i* played on day *t-1*. It is equal to the number of goals scored by country *i* minus the goals scored by its opponent. The results can be found in Table III of section 4.

To finalize our analysis, we study the duration of the effect using the following equation:

$$(10)\ \hat{\varepsilon}_{it} = \beta_0 + \beta_W \times Win_{it-2} + \beta_L \times Loss_{it-2} + u_{it}$$

This regression allows us to assess the effect of wins and losses two days after the game. Therefore, Win_{it-2} ($Loss_{it-2}$) will assume the value of 1 if country *i* won (lost) a game on day *t-2* and 0 otherwise.

4 Results

4.1 Descriptive Statistics

Table I illustrates some information regarding the number of games, mean of returns and its respective standard deviation.

The mean daily log return including all days (game days and non-game days) is approximately 0.02%, with a standard deviation of 1.77%. If we exclude game days, we get a sample of 54,883 observations, with a mean return of 0.0365% and standard deviation of 1.61%. From these numbers we can observe a slightly better situation when game days are not included, since we obtain a higher return and a lower standard deviation. When accounting only game days, independently of the outcome of the game, we achieve a mean return of 0.002% with a standard deviation of 1.89%. These numbers clearly demonstrate that the mean returns after game days are much lower than the ones observed after no game days.

Regarding wins, we have a positive mean return of 0.027% for all games with a standard deviation of 2%. After a win, it is expected to find mean returns that are positive, but this only happens in seven of the fifteen situations considered in Table I, with three of them (Qualification Games, World Cup Elimination Games and Copa America Group Games) being higher than the mean return for No Game Days. Considering the different stages of competitions, we can see that the mean returns are positive for qualifying and elimination games, and negative for group games. It could be reasonable to assume that the mean returns would be higher when associated with more advanced stages of the competition; however, we do not verify a clear pattern associated with wins, although the mean return improves when we compare the group and elimination games. Regarding the standard deviations, we can see that its value is decreasing with game importance: 1.91%, 1.90% and 1.64% for qualification, group and elimination games, respectively. This pattern regarding the standard deviations is similar to one observed in Edmans et al. (2007), although with higher values in our study.

Concerning losses, we can see a clear pattern of negative mean returns along Table I. For all games, we have a mean return of -0.23% with a standard deviation of

1.84%. This represents a great difference when compared with the mean return associated with No Game Days, being, approximately, six times higher in absolute value. If we compare the three stages of competition, we see that the mean returns decrease with game importance: 0.0163%, -0.3666% and -0.4889% for qualification, group and elimination games, respectively. This result indicates that returns following losses tend to get worst as the competition advances, and it is in accordance with Edmans et al. (2007) findings.

When comparing the mean returns of wins with the ones of losses, we observe that most of the returns following wins are higher than the ones following losses (11 out of 15). If we compare both returns in absolute value, then in the majority of the situations described in Table I (11 out of 15) the mean returns of losses are larger than the mean returns associated with wins. This result is also in accordance with Edmans et al. (2007), that states that the effect of losses is more pronounced than the effect of wins.

Table I
Daily Mean Returns and Standard Deviations for No Game Days, Wins and Losses

	No Games			Wins			Losses		
	Observations	Mean	Std. Dev.	Observations	Mean	Std. Dev.	Observations	Mean	Std. Dev.
No Games	54883	0.000365	0.016115						
All Games				907	0.000271	0.020097	235	-0.002330	0.018414
Qualifying Games				612	0.000416	0.019133	103	0.000163	0.016159
World Cup				392	-0.000108	0.021232	69	-0.002806	0.015261
European Cup				189	0.002049	0.014550	28	0.005738	0.017884
Asian Cup				31	-0.002913	0.014893	6	0.008284	0.007578
Group Games				186	-0.000408	0.019040	63	-0.003666	0.015947
World Cup				91	-0.000593	0.022573	32	-0.005518	0.018655
European Cup				48	-0.001211	0.008318	22	-0.001135	0.008101
Asian Cup				19	0.000243	0.025416	2	-0.005340	0.005394
Copa America				28	0.001128	0.015173	7	-0.002679	0.023483
Elimination Games				109	0.000180	0.016393	69	-0.004889	0.019038
World Cup				63	0.003692	0.017267	36	-0.002762	0.017998
European Cup				22	-0.004247	0.014310	20	-0.002170	0.013833
Asian Cup				10	-0.002599	0.016167	7	-0.009237	0.013175
Copa America				14	-0.006682	0.012215	6	-0.021647	0.036062

4.2 Econometric Approach

In this section we analyze the results obtained from the methodology explained previously in section *3.2*. The results are exposed in Tables II and III.

Panel A of Table II illustrates the results of equation (3) taking in account all games in our sample and also making a distinction between different stages of the competition.

Firstly, for all games, both the coefficients associated with wins and losses are negative, however only the loss coefficient is statistically significant. Besides being statistically significant at the level of one percent, the loss coefficient is, approximately, 7.5 times larger than the win coefficient. This result supports the idea that losses have a more pronounced effect than wins.

Considering only qualification games, we verify the same situation. Both coefficients are negative, with the loss one being statistically significant at five percent. Analyzing the qualification stage of different competitions, only the losses in qualification games for the World Cup are statistically significant.

Although group and elimination games in general are not statistically significant, the behavior of the win coefficient supports the idea that advanced stages of the competitions have a larger impact in returns, since we witness an increasing trend with game importance. For losses, however, we have a different behavior. We observe a decrease in the daily abnormal returns when the teams advance from qualification to group games, but from group to elimination games the coefficient for losses, unexpectedly, becomes positive. When we look for each competition in particular, this pattern is not so clear.

One possible reason for this and for the lack of statistical significance of group and elimination games is that the number of games observed for both these stages (249 for groups and 178 for eliminations) are much lower than the number of games observed for the qualification phase (715). Therefore, the impact of the games' results played during the group and elimination stages might be underestimated.

We can also notice that for all the different scenarios reported in Panel A, the majority of the coefficients for both wins and losses are negative. This result differs from other authors that have found a positive, yet not statistical significant, coefficient for wins. Since we are using the variables Win and Loss in the regression, it means that our group base is constituted by Draws and, therefore, it would be expected to find a positive sign associated with the win coefficient. However, this is not the case and the negative sign represents that the effect of draws in the returns is larger than the one of wins. However, the findings in Panel A are consistent with the fact that the daily mean return is slightly higher when we exclude game days, as stated in section *4.1*.

Equations (4) and (5) assess the effect of home and away games and their results are displayed in Table II, Panel B.

For both equations we find negative coefficients for wins and losses, but only the losses are statistical significant, which is in accordance with the results from Panel A. Once again, the loss coefficient is larger, in absolute value, than the win coefficient, reinforcing the hypotheses that losses have more impact in the returns than wins.

Since the team that plays at home usually has the majority of the support from the stands and, due to that, the supporters are more confident of a win, it is expected that a home loss incites a larger impact than an away loss. Using the same reasoning, an away win should be more important than a home win. The results of both equations sustain this idea. The coefficient for home losses is larger, in absolute value, than the one for away losses. Regarding wins, the coefficient of away wins is smaller, in absolute value, than the one of home wins.

In Panel C and C2 of Table II we can observe the results of equations (7) and (8), that evaluates the impact of the expectancy of a game's outcome, by using the method of the Elo Ratings and the Betting Odds, respectively.

Theoretically, an unexpected event should have a larger impact in the daily returns; however, the results do not support this reasoning. Once again, all the coefficients are negative, and only the coefficient associated with expected losses is statistical significant. From Panel C we observe that expected losses have a more pronounced effect in daily returns than unexpected losses. A different situation is verified for wins, with the coefficient for expected wins being smaller than the one for unexpected wins, in absolute value. Therefore, from the results of equations (7) and (8), using the Elo Ratings method, we can state that expected losses and unexpected wins have more influence in the daily returns.

From Panel C2, we can observe that the results of regressions (7) and (8) are slightly different when using the Betting Odds. In what concerns to losses, none of them are statically significant but the conclusion is the same: an expected loss have a larger impact than an unexpected one. However, in the win side, we have a coefficient that is negative for expected wins and positive for unexpected wins. These results verify that the impact of an unexpected win is larger than the one of an expected victory, which makes more sense in theory.

In the last panel of Table II the results of equation (3) are shown for three different time periods, already mentioned in section *3.2*. The results from Panel D try to assess if the effect of wins and losses have been decreasing over time, as Ashton et al. (2011) concluded.

According to Panel D, only in the subsample from 2000 to 2007 we find coefficients that are statistically significant. In this period both win and loss coefficients are negative, with the loss one being larger, in absolute value. However, this time, both coefficients, for wins and losses, are statistical significant at the level of one percent.

A possible explanation for this behavior is that it was during the period between 2000 and 2007 that most studies analyzing the effect of football in the economy were published. These studies might have triggered the attention of investors who, for a period of time, started to take in account these effects.

Another explanation is the importance of the media. In the early 2000's we witnessed some innovations in the media coverage of football events, like the broadcast of the route of the team's bus from the training center to the stadium. These innovations increased the level of identification between supporters and their national teams and, as Wann et al. (1994) concluded, as the identification with the team increases, the impact of the team's results on supporters will also increase. Since the period between 2000 and 2007 is characterized by these innovations in the broadcasting of football events and an increase in the level of identification with the national teams, it is normal to find that both wins and losses are statistically significant. However, the sign of the win coefficient continues to be negative.

Table III exposes the results for equation (8). This equation measures if the goal difference has an impact in the abnormal returns, and also measures if the intensity of the result has a linear or nonlinear effect.

In the first line of the table, we can observe that the results achieved are similar to the ones of Castellani et al. (2013) and the interpretation for the signs of the coefficients is the same. The coefficient associated with the linear term is positive, which is consistent with the preference for wins over losses. The coefficient of the quadratic term is negative, which means that the abnormal returns increase less than proportionally with the goal difference. This fact might occur due to two reasons: first, rarely the goal difference has an important impact in the competitions; second, a large goal difference might translate a huge disparity in the quality of the teams, reducing the importance of the game.

When we only consider group games, the signs of the coefficients changed. In this stage of competition the goal difference can have a significant impact to determine which teams advances to next stage and, therefore, it is understandable that coefficient associated with the quadratic term is positive. However, the negative sign of the linear term is unexpected, since it does not demonstrate a preference for wins over losses.

As final note, it is important to understand that these interpretations are speculative, since the results are not statistically significant.

Concerning our last regression, regression (10), the results are as follows: the win coefficient is -0.034475, with a standard deviation of 0.032711, and the loss coefficient is -0.077415, with a standard deviation of 0.063876. These values give us the t-Values for wins and losses, that are, respectively, -1.053946 and -1.211951. Therefore, both wins and losses are not statistical significant, which means that the effect of football results is of a very short duration and is only realized in the day that follows a game day.

Table II
Abnormal Daily Return Performance

	Wins				Losses			
	Observations	β_W	Std. Dev.	t-Value	Observations	β_L	Std. Dev.	t-Value
				Panel A: Type of Game				
All Games	907	-0.023737	0.032712	-0.725637	235	-0.177981	0.063879	-2.786217 *
Qualifying Games	612	-0.104122	0.099550	-1.045925	103	-0.342028	0.167080	-2.047086 **
World Cup	392	-0.068417	0.094510	-0.723907	69	-0.247153	0.142603	-1.733154 ***
European Cup	189	-0.087574	0.151409	-0.578393	28	-0.029814	0.228512	-0.130468
Asian Cup	31	-0.366727	0.635724	-0.576865	6	0.107671	0.711478	0.151335
Group Games	186	-0.113811	0.25056	-0.454227	63	-0.662326	0.445244	-1.487556
World Cup	91	-0.055535	0.212334	-0.261544	32	-0.123027	0.26462	-0.464921
European Cup	48	-0.312311	0.204898	-1.524229	22	-0.342511	0.234435	-1.461009
Asian Cup	19	0.247496	0.355131	0.696914	2	-0.270728	0.686069	-0.394607
Copa America	28	-0.282958	0.413260	-0.682520	7	-0.463632	0.522737	-0.886930
Elimination Games	109	0.303047	0.188892	1.604338	69	0.575196	0.495280	1.161356
World Cup	63	0.136734	0.146487	0.933422	36	-0.165965	0.190191	-0.872624
European Cup	22	-0.328379	0.275339	-1.192635	20	-0.278634	0.282138	-0.987578
Asian Cup	10	-0.332850	0.307217	-1.083437	7	-0.442641	0.367194	-1.205469
Copa America	14		0.258985	-1.213756	6	-1.146583	0.395606	-2.898295 *
				Panel B: Site of Game				
Home Games	GG	-0.064322	0.068031	-0.945474	33	-0.410042	0.192119	-2.134315 **
Away Games	EG	-0.013922	0.060604	-0.229727	202	-0.144841	0.084235	-1.719477 ***
				Panel C: Result Expectancy (Elo Rating)				
Expected Result	866	-0.021893	0.059298	-0.369208	101	-0.305649	0.115183	-2.653589 *
Unexpected Result	41	-0.097598	0.158135	-0.617181	134	-0.080201	0.096308	-0.832749
				Panel C2: Result Expectancy (Betting Odds)				
Expected Result	393	-0.002584	0.073487	-0.035159	34	-0.097091	0.162993	-0.595678
Unexpected Result	25	0.054581	0.181515	0.300698	86	-0.056285	0.102944	-0.546753
				Panel D: Year Effect				
1993 - 1999	259	0.080294	0.061249	1.310954	67	-0.076231	0.119784	-0.636408
2000 - 2007	360	-0.163015	0.051383	-3.172527 *	90	-0.456873	0.102096	-4.474910 *
2008 - 2014	288	0.061440	0.058667	1.047262	78	0.061866	0.112037	0.552192

* Statistically significant at 1%; ** Statistically significant at 5%; *** Statistically significant at 10%

Table III
The effect of Goal Difference in the Abnormal Daily Return

	Goal Difference			Goal Difference²		
	β_1	Std. Dev.	t-Value	β_2	Std. Dev.	t-Value
All Games	0.010292	0.016728	0.615240	-0.001855	0.002548	-0.728036
Qualifying Games	0.012810	0.026725	0.479324	-0.003446	0.003364	-1.024488
Group Games	-0.028965	0.032208	-0.899325	0.010863	0.007855	1.382904
Elimination Games	0.002594	0.044067	0.058856	-0.001964	0.012337	-0.159169

* Statistically significant at 1%; ** Statistically significant at 5%; *** Statistically significant at 10%

To conclude this section, we have redone all the methodology previously presented, but assuming that the error term of the GARCH models for each country follows a t-Student distribution, instead of a normal distribution. We also decided to analyze the year effect by using three different dummy variables, instead of dividing our sample in three subsamples.

The results obtained with these new regressions are almost identical as the ones presented before and, for that reason, the conclusions are also the same. Due to the absence of a significant difference in the results obtained, these are not displayed in this study.

5 Conclusions

This work was motivated by the number of studies that found a relationship between sports and the economy, and it analyzes the effect of football in the stock market's returns, using the games' outcomes as a variable of mood.

We found statistical evidence that losses can affect the stock markets' returns of the day following a game day, however, the effect of wins do not have any statistical significance. We also observed that the coefficient associated with losses is larger, in absolute value, than the one associated with wins. These results were already expected due to the loss aversion and because losses usually trigger a range of emotions associated with visceral factors, which drives people to make impulse decisions (Loewenstein (1996, 2000)).

A surprising result is the absence of a statistically significant sign associated with the win coefficient. A significant positive coefficient was expected since winning is the outcome that football supporters usually want.

Without any surprise, we verify that the site of the competition is relevant and statistically significant for losses. Losses at home and away are statistically significant at the level of 5% and 10%, respectively. The coefficient for losses at home is larger than the one for away losses, as we expected.

In this study we also decided to analyze the effect of the result's expectancy. In theory an unexpected event would trigger a more pronounced reaction; however, our results show the opposite. When using the Elo ratings, expected losses are statistically significant and have a larger coefficient, in absolute terms, than unexpected losses. Using the betting odds, we do not find any statistical significant result, which might be explained by the shorter number of games included, since we did not have access to the odds of all the games included in our study.

All the effects described above are short-term effects, which are only relevant in the day after the game. This conclusion comes from the results of equation (10) that does not show any result that is statistical significant.

To finalize, we studied the effect of the games' outcomes over the years. What we conclude is consistent with the results of Ashton et al (2011), which claimed that the importance of this effect had been decreasing over the years.

Although some of the results of this work are below our expectations, it is important to highlight the fact that the study still shows evidence of a short-term effect of the games' outcome in the stock market. This effect, even though it might be only applicable to some investors, represents that there are non-fundamental economic factors that could make investors act irrationally and, therefore, affect the stock markets' returns in a predictable sense, as stated by the field of behavioral finance.

6 References

Abel, A. B. (2002). An exploration of the effects of pessimism and doubt on asset returns. *Journal of Economic dynamics and control*, 26(7), 1075-1092.

Arkes, H. R., Herren, L. T., & Isen, A. M. (1988). The role of potential loss in the influence of affect on risk-taking behavior. *Organizational behavior and human decision processes*, 42(2), 181-193.

Ashton, J. K., Gerrard, B., & Hudson, R. (2003). Economic impact of national sporting success: evidence from the London stock exchange. *Applied Economics Letters*, 10(12), 783-785.

Ashton, J. K., Gerrard, B., & Hudson, R. (2011). Do national soccer results really impact on the stock market?. *Applied Economics*, 43(26), 3709-3717.

Bernile, G., & Lyandres, E. (2011). Understanding investor sentiment: The case of soccer. *Financial Management*, 40(2), 357-380.

Berument, H., Ceylan, N. B., & Gozpinar, E. (2006a). Performance of soccer on the stock market: Evidence from Turkey. *The Social Science Journal*, 43(4), 695-699

Berument, H., Ince, O., & Yucel, E. M. (2006b). Success in soccer and economic performance: Evidence from Besiktas-Turkey. *Rivista Internazionale di Scienze Economiche e Commerciali*, 53(2), 260-274.

Boido, C., & Fasano, A. (2007). Football and mood in Italian stock exchange. *Review of Financial Studies*, 14, 1-27.

Boyle, G., & Walter, B. (2003). Reflected glory and failure: International sporting success and the stock market. *Applied Financial Economics*, 13(3), 225-235.

Carroll, D., Ebrahim, S., Tilling, K., Macleod, J., & Smith, G. D. (2002). Admissions for myocardial infarction and World Cup football: database survey. *BMJ: British Medical Journal*, 1439-1442.

Castellani, M., Pattitoni, P., & Patuelli, R. (2013). Abnormal returns of soccer teams and event clustering: reassessing the informational value of bets. *Journal of Sports Economics*, 16, 735-759.

Chandler, R. (2006). The impact of sport on the workplace. A research report commissioned by Hudson, June.

Edmans, A., Garcia, D., & Norli, Ø. (2007). Sports sentiment and stock returns. *The Journal of Finance*, 62(4), 1967-1998.

FIFA (2014). *The 2014 FIFA World Cup in Numbers.*

Available in: http://resources.fifa.com/mm/document/tournament/competition/02/44/29/89/fifaworldcupinnumbers_120714_v7_eng_neutral.pdf [Last accessed at: 27-02-2016]

FIFA(2015). *2014 FIFA World Cup Brazil: Television Audience Report.*

Available in: http://resources.fifa.com/mm/document/affederation/tv/02/74/55/57/2014fwcbraziltvaudiencereport(draft5)(issuedate14.12.15)_neutral.pdf [Last accessed at: 27-02-2016]

Hirshleifer, D. (2001). Investor psychology and asset pricing. *The Journal of Finance*, 56(4), 1533-1597.

Hirshleifer, D., & Shumway, T. (2003). Good day sunshine: Stock returns and the weather. *The Journal of Finance*, 58(3), 1009-1032.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica: Journal of the econometric society, 263-291.

Kamstra, M. J., Kramer, L. A., & Levi, M. D. (2000). Losing sleep at the market: The daylight saving anomaly. *The American Economic Review*, 90(4), 1005-1011.

Kaplanski, G., & Levy, H. (2010). Exploitable predictable irrationality: the FIFA World Cup effect on the US stock market.

Klein, C., Zwergel, B., & Henning Fock, J. (2009). Reconsidering the impact of national soccer results on the FTSE 100. *Applied Economics*, 41(25), 3287-3294.

Loewenstein, G. (1996). Out of control: Visceral influences on behavior. *Organizational behavior and human decision processes*, *65*(3), 272-292.

Loewenstein, G. (2000). Emotions in economic theory and economic behavior. *The American Economic Review*, 90(2), 426-432.

Odean, T. (1998). Are investors reluctant to realize their losses?. *The Journal of finance*, 53(5), 1775-1798.

Pantzalis, C., & Park, J. C. (2014). Exuberance out of left field: Do sports results cause investors to take their eyes off the ball?. *Journal of Economic Behavior & Organization*, 107, 760-780.

Saunders, E. M. (1993). Stock prices and Wall Street weather. *The American Economic Review*, 83(5), 1337-1345.

Schwarz, N., Strack, F., Kommer, D., & Wagner, D. (1987). Soccer, rooms, and the quality of your life: Mood effects on judgments of satisfaction with life in general and with specific domains. *European Journal of Social Psychology*, 17(1), 69-79.

Shefrin, H., & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *The Journal of finance*, 40(3), 777-790.

Statman, M. (2014). Behavioral finance: Finance with normal people. *Borsa Istanbul Review*, 14(2), 65-73.

Stracca, L. (2004). Behavioral finance and asset prices: Where do we stand?. *Journal of Economic Psychology*, *25*(3), 373-405.

Thaler, R. H. (1999). The end of behavioral finance. *Financial Analyst Journal*, 55(6), 12–17.

Wann, D. L., Dolan, T. J., McGeorge, K. K., & Allison, J. A. (1994). Relationships between spectator identification and spectators' perceptions of influence, spectators' emotions, and competition outcome. *Journal of Sport and Exercise Psychology*, 1(6), 347-364.

7 Appendix

7.1 General Information

Country	Index	Type of Index	Datastream Code	Total Games	Wins	Losses	Draws
South Korea	Kospi	Price Index	KOR200I	131	72	27	32
Japan	Nikkei 225	Price Index	JAPDOWA	131	84	24	23
Argentina	Merval	Price Index	ARGMERV	151	88	32	31
Brazil	Bovespa	Total Return Index	BRBOVES	138	93	21	24
Netherlands	AEX	Price Index	AMSTEOE	149	105	26	18
France	CAC 40	Price Index	FRCAC40	136	78	24	34
Germany	DAX 30	Price Index	DAXINDX	149	106	17	26
England	FTSE 100	Price Index	FTSE100	129	74	26	29
Spain	IBEX 35	Price Index	IBEX35I	153	114	15	24
Portugal	PSI 20	Price Index	POPSI20	150	93	23	34

7.2 Price Index

Datastream's Price Index is computed as follows:

$$I_t = I_{t-1} \times \frac{\sum_{1}^{n}\left(P_t \times N_t\right)}{\sum_{1}^{n}\left(P_{t-1} \times N_t \times f\right)}$$

Where:

- I_t = index value at day t;

- I_{t-1} = index value on previous working day;

- P_t = unadjusted share price on day t;

- P_{t-1} = unadjusted share price on previous working day;

- N_t = number of shares in issue on day t;

- f = adjustment factor for a capital action occurring on day t;

- n = number of constituents in index.

7.3 Total Return Index

Datastream's Total Return Index is computed as follows:

$$RI_t = RI_{t-1} \times \frac{PI_t}{PI_{t-1}} \times \left(1 + \frac{DY}{100 \times n}\right)$$

Where:

- RI_t = return index on day t;

- RI_{t-1} = return index on previous day;

- PI_t = price index on day t;

- PI_{t-1} = price index on previous day;

- DY = dividend yield of the price index;

- n = number of days in financial year (usually 260).