INVESTOR SENTIMENT AND STOCK RETURNS

THE EFFECT OF EUROPEAN SOCCER RESULTS

Daisy de Vries (347526)
Supervisor: Aurélien Baillon
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ABSTRACT

This paper investigates the effect of changes in investor sentiment, caused by soccer results, on stock returns. According to the behavioral finance framework, investors are not fully rational, and their mood influences the way they make decisions on the stock market. If soccer results affect investor sentiment, this effect should be reflected in stock prices the first trading day after a match. I study the soccer results of 28 countries during 10 European Championships, but I do not find a relation between soccer results and stock prices, and these results seem to be robust to methodological changes.

Preface

This master thesis is the final work of my master study Behavioral Economics at the Erasmus School of Economics in Rotterdam. In this thesis, I have tried to apply everything I have learned over the past year(s) and to conduct an interesting and comprehensive research study that contributes to the existing literature on the relationship between investor mood and stock returns.

Although there are many events linked to investor mood, I have chosen to examine the effect of soccer results. I am a soccer fan myself, and fascinated by the impact it has on many people's lives. I speak from my own experience when arguing that soccer results can have a considerable influence on a person's mood, and it seemed interesting to me to examine whether this effect was also reflected on stock markets.

As I liked my topic a lot, I enjoyed writing my thesis most of the times. It was interesting to learn about the existing research on investor sentiment and the versatile events that were found to influence mood. Furthermore, I have learned a lot about statistics and conducting research, which will be useful in my future career.

I would like to thank Aurélien Baillon, my supervisor, for his support, feedback and useful advice during this process.

Daisy de Vries
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1. Introduction

Every Dutchman recalls the night of July 11th, 2010, when the Dutch soccer team lost the World Cup final against Spain. The national deception that followed was enormous and endured for at least a couple of days. The view that soccer, and sport in general, has an impact on many people's lives is supported by an abundance of research and statistics. Branscombe and Wann (1991) show that sport increases feelings of self-worth and belonging and makes people feel less depressed. To illustrate the popularity of soccer, 299 million people watched the 2012 European Championship final between Italy and Spain, and the 2006 World Cup in Germany had a cumulative television audience of 26 billion. For many countries, soccer is of 'national interest', and therefore it is likely that soccer matches also influence the mood of investors in a country. Research by Shu (2010) shows a positive relation between mood and stock prices, suggesting that if soccer results have an impact on investor mood, this effect should also be visible on stock markets.

The existing literature on the effect of soccer results on stock returns is mixed. The leading paper on this topic by Edmans, García and Norli (2007) studies World and continental cups and finds a negative stock reaction after a loss, but no effect after a win. This finding is consistent with the concept of loss aversion, which implies that the negative reaction after a loss is larger than the positive reaction after a gain. Other studies examining this effect report contrary results and argue that soccer results do not affect local stock markets. To contribute to the existing literature, and because there has been no study focusing on this effect in Europe so far, it is interesting to investigate the effect of European soccer results on local stock market returns.

In this study, I will examine whether sudden changes in investor mood, caused by European soccer results, affect stock returns. The research question of this paper is as follows:

What is the effect of European soccer results on local stock markets?

Investigating European soccer results of 28 countries from 1974 to 2012, I do not find evidence that the results of soccer matches have an effect on local market stock returns. Besides looking at the effect of a win and loss in general, I also study specific rounds during a tournament and examine whether countries that have a larger interest in soccer events experience a stronger stock market reaction after soccer outcomes, but my results remain insignificant. The fact that the home bias has decreased after 2002, and European investors invest less in their country's local stock market does not seem to have an affect on this relationship. Contrary to Edmans, García and Norli (2007), this research indicates that local market stock returns are unaffected by soccer results, nor do I find evidence for the loss effect. The results of this study do not give rise to a violation of the Efficient Market Hypothesis.

The remainder of my paper is as follows. In section 2, I will give an overview of the existing literature that serves as the foundation for my research. Moreover, I will explain the two main behavioral biases applicable to my paper and the hypotheses I will test. In section 3, I will elaborate on my dataset, consisting of daily stock returns and soccer results of 28 European countries and explain the methodology I apply to analyze my data. The results of these analyses are reported in section 5. I state my conclusion in section 6 and give some comments and recommendations in section 7.

2. Literature review

2.1 Efficient market hypothesis and anomalies

For many years, the traditional finance paradigm has been the standard to explain movements in the stock market. Within this paradigm, agents are assumed to be rational, which means that if they receive new information, they update their beliefs immediately and correctly, and they make choices consistent with the Expected Utility framework (Barberis & Thaler, 2003). In other words, they make choices that maximize their expected utility, and apply Bayesian decision-making, which is a consequence of the Expected Utility framework. According to Bayes' theorem, agents use the knowledge they gained from previous experiences to assess the probability of future events (Dempster, 1968). For example, if age and the probability of getting ill are related, an agent can use someone's age to assess the probability of getting ill.

In this traditional framework, Fama's Efficient Market Hypothesis (EMH) states that market are efficient, and that actual prices reflect fundamental values. Moreover, it is not possible for investors to earn excess returns as all relevant information is incorporated in stock prices. Within EMH, there are thee forms. The first is the weak form and implies that stock prices reflect all market information. This form argues that stock prices follow a random walk, which means they are unpredictable. As stock prices do not depend on prior stock prices, investors can not use information about past stock prices to earn excess returns. According to the semi strong form, stock prices reflect all publicly available information, and investors absorb new information immediately, so that investors can not use this public information to earn excess returns. As news is unpredictable, this form of EMH argues that prices should be unpredictable too and thus random. Finally, the strong form implies that stock prices reflect both private and public information, making it impossible to earn excess returns at all. According to EMH, mispricing can not persist, as rational investors would correct this mispricing immediately by performing arbitrage (Fama, 1970).

Over the past decades, there have been many anomalies that could not be explained by the Efficient Market Hypothesis. One type of anomalies is the calendar effect, which refers to anomalies in stock returns related to time periods, as specific months, days or years. Well-known effects are the January effect, the Weekend effect and the Monday effect. According to EMH, these anomalies could not exist because time periods are known in advance so investors can not benefit from trading on this public information. Moreover, rational investors would immediately correct mispricing on the stock market, but several papers have shown that this is not the case.

During the Internet bubble at the end of the 20^{th} century, investors were able to exploit mispricing and earn excess returns for a long time period. From early 1998 to February 2000, the Internet sector earned over 1.000% returns on its equity (Ofek & Richardson, 2003) and stock prices of companies with '.com' in their name rose far above fundamental value. As EMH argues, stock prices reflect fundamental values and change only when new information becomes available. However, there was no news during that period that was proportionate to the enormous increase in stock prices. By the end of 2000, investors started selling these stocks, and the complete sector crashed.

An anomaly that illustrates a violation of the Expected Utility Framework is the Equity Premium Puzzle by Mehra and Prescott (1985). This paper addresses the significantly high returns on stocks compared to 'risk-free' bonds over the past decades. This puzzle shows that investors exhibit an irrational high level of risk aversion, which leads to undervaluation of stocks. The traditional finance framework is not able to explain this puzzle, as under this theory, investors are rational and can not earn excess returns for a longer period of time.

As Fama argues in "Efficient Markets II" (1991), it can be difficult to test market efficiency because of the Join-Hypothesis problem. According to this theory, it is not possible to test market efficiency in isolation, as it is always tested together with an underlying asset-pricing model to compute expected stock market returns. Consequently, if an anomaly is found that can be interpreted as evidence against market efficiency, it could also be the case that a wrong asset-pricing model is used, but that markets are efficient.

Despite Fama's argument, the Efficient Market Hypothesis could not explain these anomalies and researchers started looking for alternative explanations. As Schleifer explains in his book "Inefficient Markets" (2001), numerous studies have challenged the foundations of the Efficient Market Hypothesis and the empirical evidence to support this theory since.

As a response to the difficulties faced by the traditional finance paradigm, behavioral finance emerged as an alternative view on financial markets. In this theory, financial markets are not expected to be efficient, but there are some major deviations from this efficiency that persist over a long period of time, mainly caused by investor behavior. In essence, behavioral finance is based on two main assumptions. First, limits to arbitrage, which implies that arbitrage is far from perfect, as it might be costly and risky to perform and therefore, investors may be reluctant to benefit from mispricing. The second assumption is investor sentiment, which concerns how investors actually form their beliefs and expectations. Contrary to the traditional paradigm, investors are bounded rational, which implies that due to limited information, time and cognitive capabilities, agents do not always make choices that are fully rational and agents can not always accurately predict the likelihood of an event. Rather, they rely on rules of thumb and other factors, like their mood to make decisions. Examples of rules of thumbs they apply are the representativeness bias and the availability bias. The representativeness bias describes the tendency to assign a higher probability to an event if it represents a certain stereotype, instead of considering the objective probability that an event will happen. With the availability bias, people assign a higher probability to events that come easier to mind (Barberis & Thaler, 2003). These heuristics are helpful tools to make decisions, but prevent investors from being fully rational and violate Bayes' theorem, as they are unable to accurately predict the likelihood of an event.

Behavioral finance helps understanding anomalies as the preference of cash dividend (Shefrin & Statman, 1984) and the comovement of stocks (Barberis et al., 2005), using investor sentiment and bounded rationality as underlying foundations, rather than assuming efficiency and rationality in today's stock markets.

2.2 Investor psychology and stock pricing

In behavioral finance, there has been extended research on investor mood and asset pricing. However, according to the Efficient Market Hypothesis, stock prices should only change when new relevant information becomes available and since investors are expected to be rational, their mood should not influence their behavior on the stock market.

Loewenstein (2000) finds that emotions have important, but underappreciated consequences for behavior. This paper argues that emotions and feelings often result in behavior that differs from weighing the long-term costs and benefits of actions. Lucey and Dowling (2005) link these conclusions to equity pricing, by arguing that equity pricing involves the process of weighing the long terms costs and benefits, and state that it is likely that emotions and feelings of investors have an influence of the way they price assets. Shu (2010) explores this effect of mood on stock prices and finds a positive effect that links higher asset prices with better mood. Conversely, expected asset returns correlate negatively with investor mood, as a good mood leads to less risk aversion. These results indicate that investor mood is an important determinant for explaining investor behavior that can not be explained within the traditional finance paradigm.

In order to measure investor mood, researchers link returns to events that are likely to impact mood. For example, Kamstra, Kramer and Levi (2000) research the effect of daylight saving on stock returns and find that the disrupted sleep patterns caused by daylight saving affect several international financial stock markets. In the U.S. for example, this effect accounts for a one-day loss of $31 billion on the NYSE, NASDAQ and AMEX exchanges.

Also non-secular holidays impact investor behavior and thus stock returns. Frieder and Subrahmanyam (2004) look at stock prices in the U.S. market around religious and cultural occasions as St. Patrick’s Day and the Jewish High Holy Days of Rosh Hashanah and Yom Kippur. They find higher returns on the days preceding St. Patrick’s Day and Rosh Hashanah and negative returns the days after Yom Kippur, consistent with the view that investor mood is an explanation for changes in asset pricing.

Yuan, Zheng and Zhu (2006) explore lunar cycles and find that these influence investor mood as well. They report that stock returns are lower on days around a full moon than on the days around a new moon, and that this effect is independent of other calendar-related anomalies as the January effect and the calendar month effect.

Cao and Wei (2005) study the effect of temperature on stock market returns. They expect lower temperatures to lead to aggression, which could result in more risk-taking, and higher temperature to lead to both apathy and aggression, where the effect of apathy is stronger than the effect of aggression, associated with less risk-taking behavior. Their results show a negative relation between temperature and returns, indicating that lower temperatures lead to more risk-taking behavior and higher stock returns.

First Saunders (1993) and later Hirshleifer and Shumway (2003) examine whether stock prices are influenced by the weather. Research by Saunders (1993) shows a high correlation between the weather in New York and major stock indexes and supports the view that investor sentiment influences stock prices. Saunders' results appeared to be robust with the January, weekend and small-firm effects and can be interpreted as further evidence that stock markets are not entirely rational.

Hirshleifer and Shumway (2003) extend the work of Saunders and find that sunshine is highly correlated with daily stock returns, indicating that the level of sunshine positively affects investor mood. After they controlled for sunshine, they do not find such a relation for other weather conditions, like snow and rain.

The question is however, whether investors can benefit from trading on the weather, as this strategy concerns frequent trading, and the transaction costs involved probably would eliminate this benefit. Still these papers deliver a meaningful contribution in understanding the factors that influence investor behavior.

2.3 International soccer results as a mood variable

Another event that is likely to impact mood and used to investigate the relation between investor sentiment and stock returns are soccer matches.

Edmans, García and Norli (2007) state three conditions a mood variable must satisfy to be linked with stock returns, and argue that soccer results satisfy all of them. "First, the variable must impact mood in a substantial and unambiguous way, so that its effect is strong enough to show up in stock prices. Second, the majority of a population should be impacted by this variable, so that it affects enough investors. Finally, the effect must be correlated across the majority of people in a country" (Edmans, García & Norli, 2007).

A study by Dolan and McGeorge (1994) shows that spectators who identify themselves with a sports team have a greater perception of influencing the outcome of the game. Moreover, these fans experience strong positive emotions following a win of their favorite team and an increase in negative emotions following a loss. Branscombe and Wann (1991) find that sport enhances people's self-esteem, identification, and the related feeling of belonging, which makes them feel less depressed or alienated and increases their self worth.

Looking at statistics on television audience during soccer events further confirms the popularity of soccer. According to FIFA (The Fédération Internationale de Soccer Association), the 2006 World Cup in Germany had a cumulative total television audience of 26 billion people[1]. Moreover, UEFA (The Union of European Soccer Associations) reported that 299 million people worldwide watched the 2012 European Championship final between Spain and Italy. In the UK, the match between England and Italy that year attracted on average 20.3 million viewers, beating the wedding of Prince William (13.6 million viewers).[2]

Besides the fact that soccer plays in importance role in many people's lives, it can also impact the economic activity in a country. Hosting an international soccer event has diverse economic benefits, like additional employment, sales, infrastructure development and of course increased tourism. Ahlert (2001) argues that despite the high investments in World Cup infrastructure like stadiums, hosting a World Cup positively influences income and employment in a country. Lee and Taylor (2004) report that World Cup tourists spend about 1,8 times more than foreign leisure tourists. To illustrate, the World Cup 2006 in Germany generated $900 MLN net national tourism income (Allmers & Maennig, 2009). In other words, soccer also affects a country from a rational point of view, as it is likely that organizing a tournament of this size has an impact of a country's economy.

These studies and statistics confirm the view that soccer events are likely to affect people's mood, and can also impact the economic activity of a country.

1 http://www.fifa.com/mm/document/fifafacts/ffprojects/ip-401_06e_tv_2658.pdf
2 http://www.uefa.com/uefaeuro/news/newsid=1834666.html

2.4 The effect of soccer results on stock returns

In the previous years, several papers have used international soccer results as a mood variable and researched the relation between soccer results and stock returns.

The main paper that investigates the effect of international soccer results on the stock market is the study by Edmans, García and Norli (2007). They look at World Cups and continental cups and find that lost soccer matches have an economically and statistically negative effect on the losing country's stock market. In monthly terms, the excess returns associated with a soccer loss are more than 7%. They do not find a positive effect for wins, which is are consistent with prospect theory that states that losses loom larger than gains. They also test the effect on match outcomes on stock returns for other sports as cricket, rugby and basketball games and find similar results.

Kaplanski and Levi (2008) work further on the study by Edmans, García and Norli (2007) by considering the U.S. market instead of the two local markets of the countries that played a game. In every given country, there is a relatively large part of investors investing in international markets, like the U.S. market. The authors argue that if there is a negative investor sentiment due to a country's loss during a soccer event, this should also be reflected on the U.S. market. Kaplanski and Levi look at the aggregate effect of all local effects and find that the World Cup effect is large, highly significant and long lasting. From 1950 to 2007, the average return on the U.S. market on World Cup days is -2,58% compared to +1,21% on non- World Cup days. This indicates that the aggregate effect can be predicted and is exploitable, since it is negative over all tournaments and known in advance.

Several researchers have also examined this effect for specific countries, especially countries where soccer is an important national sport. Ashton, Gerrard and Hudson (2003) chose to investigate stock returns in England, and report a strong association between international soccer results of the English national soccer team and stock prices on the London stock exchange. Similar to the study by Edmans, Garcia and Norli (2007) and consistent with the concept of loss aversion, this effect is only significant for losses.

Klein, Zwergel and Heiden (2009) reply to this paper and argue that the significant results found by Ashton, Gerrard and Hudson (2003) are not robust. Consequently, they find no link between soccer results and stock returns, and conclude that the results found by Ashton, Gerrard and Hudson (2003) rely upon mistakes in the empirical set-up of their study.

Gallagher and O'Sullivan (2011) study Ireland to investigate the effect of soccer results on stock returns. Similar to Klein, Zwergel and Heiden (2009) they do not find a significant link after controlling for several effects.

To conclude, the link between soccer sentiment and stock returns is somewhat ambiguous, as there have been mixed results. With this study, I will elaborate on the existing literature on this topic, and try to clarify the relationship between soccer results and stock prices and in general the impact of investor mood on the stock market.

2.5 Behavioral biases

The two main behavioral theories applicable to my research are prospect theory, in particular loss aversion, and the home bias.

2.5.1 Loss aversion

The prospect theory by Kahneman and Tversky (1979) states that utility is derived from a reference point, rather than final wealth states and that agents are more sensitive to a negative deviation than a positive deviation from this point. The latter is called the loss effect and implies that the negative reaction after a loss will be larger than the positive reaction after a gain. According to this asymmetry, there should be a larger negative effect following a soccer team's loss than a positive reaction after a win.

2.5.2 Home bias

Another bias that plays a role in this research and influences investor behavior on the stock market is the home bias, which is the tendency to invest in domestic stocks. If the home bias holds, it is likely to assume that the investors in a country's local stock market are also the supporters of that country's national soccer team.

The question is whether this bias still exists in European countries, in particular in countries using the euro as a currency. While the study by Edmans, García and Norli (2007) assumes the presence of this bias, there are several papers indicating that the home bias has decreased over the past years. Giofré (2008) and Schoenmaker and Bosch (2008) find that since the entrance of the euro, the home bias decreased or almost disappeared in many countries that use the euro. Because of this new currency, it has become less costly and risky for investors in euro-countries to diversify their investments over multiple stock markets in Europe. They even introduce the term "euro bias" as a substitute for the home bias.

The presence of the home bias is an important assumption in order to link investor mood with stock returns. If investors invest in more stock markets than solely their country's local market, the effect of their negative (positive) mood after a loss (win) will also be divided over multiple stock markets. As a consequence, the link between soccer results and stock returns might become less visible on the local stock market of a country's soccer team.

2.6 Hypotheses

This research contributes to the existing literature examining the effect of international soccer results on stock market returns, following the paper by Edmans, García and Norli (2007). Similar to this research, I will study international soccer Championships for multiple countries. However, while they study World Cups and three continental cups, this study will focus on European Championships, for two particular reasons. First, European local stock markets are more similar to each other, as they operate under more or less the same laws and experience similar environments, and are therefore more comparable than local stock markets from other continents. Second, as the home bias has decreased in European countries due to the entrance of the euro, it is interesting to investigate whether this affects the results of my study.

To answer my research question stated in section 1, I will test the following hypotheses:

Hypothesis 1: European soccer results of a national soccer team have an effect on a country's local stock market.

> *Hypothesis 1.1*: A win of the national soccer team has a positive effect on the stock market of that country.
>
> *Hypothesis 1.2*: A loss of the national soccer team has a negative effect on the stock market of that country.
>
> *Hypothesis 1.3*: The negative effect after a loss of the national soccer team is stronger than the positive effect after a win.

As soccer matches are shown to have an influence on people's lives and mood, I expect to see a positive (negative) effect of a country's stock market after a win (loss). According to prospect theory, losses weigh heavier than wins, and therefore I expect the effect after a loss to be stronger.

Hypothesis 2: The effect of soccer results on local stock markets will be stronger in elimination games than non-elimination games.

There are direct consequences tied to results of elimination games, but not to non-elimination games as for these games, the final result after a couple of matches count. Therefore, I expect the effect after an elimination game to be stronger.

Hypothesis 3: The effect of soccer results on local stock markets of euro-countries will be less strong or disappear after 2002.

Due to the entrance of the euro, it has become less risky for investors from euro-countries to invest in other country's stock markets. If soccer results influence investor mood, this effect will be reflected on multiple stock markets, rather than only the investor's domestic stock market.

Hypothesis 4: The effect of soccer results on local stock markets will be stronger if the outcome of a match is unexpected, using outcome probabilities obtained by soccer ranking data.

If a country wins (loses) a match, while it was expected to lose (win), I expect the positive (negative) effect on investor mood and thus stock returns to be stronger than if the expected outcome occurs.

3. Data

To test my hypotheses, I collect data on soccer results from 10 UEFA European Championships from 1974 to 2012[3]. Moreover, I obtain daily local returns from the Total Return Index from Datastream. Since data on Total Return Indices start in 1973, I collect financial data from January 1st, 1973 to December 31st, 2012. In total, my sample consists of 28 European countries, both countries within and outside the euro zone. I will analyze this data using Stata.

3.1 European Championships

I collect data on qualification games, play-offs, group matches, quarterfinals, semi-finals and finals. Until 1992, eight countries participated in the final tournament. From 1996, there are 16 participants and from 2016, there will be 24 countries. As Datastream's Total Return Index start from 1973, the first soccer results I collect are in 1974, which are qualification games for the 1976 European Championship.

3 http://www.uefa.com/uefaeuro/finals/history/index.html

As described in table 1, there are 1.951 trading days after a match was played and 290.223 days without a match result, of which 2.576 days are holidays like Christmas and Easter. I will elaborate more on descriptive statistics in section 3.3.

3.1.1 Qualification stage

During qualification or preliminary games countries get the chance to qualify for the final tournament. The country that hosts the cup is automatically qualified for the tournament in that year and starts immediately in the group phase. The number of countries participating in the qualification games varies, but lies often between 32 and 45. The qualification stage starts about two years before the tournament. All countries are divided into groups, and the best performing countries per group are qualified for the Championship. In total, there are 1.587 trading days that are followed by a qualification game.

Play-offs are the last qualification games before the tournament. In total, my sample consists of only 18 play-off results, divided over 10 playoff matches, as they are were not played before each European Championship.

3.1.1.1 ELO Ratings

Especially during qualification games, there is a large variety in skills across the national teams, as almost every European country is allowed to participate. If one country's national team is of much better quality than its opponent, there is a very high chance that the better qualified team will win, and it is less likely that the game outcome will impact investors' mood as it is not considered as an important match. Similar to Edmans, García and Norli (2007), I use ELO ratings to select games that are likely to have an effect. The ELO ranking is a list with ratings that defines the skill of a national team, and is comparable with the more common FIFA ranking. I follow the process by Edmans, García and Norli (2007) and collect for each match the ELO ratings of the two countries and look at the difference between these rankings. A game is considered as close if the difference between the two countries' rating is less than 125 points, after adding 100 points to the team with the home field advantage. I apply this approach to qualification rounds only, as I assume the games in the next rounds to be of relevant importance.

Unfortunately, I could not find the ELO rating for some countries in my sample. If I could find the financial data for a country, but not the ELO rating, I considered the ELO rating of that country to be zero, and qualified the game as non-important. This occurred only a few times, with countries that barely participated in European Championships.

382 match results are considered as close, and 1.205 as non-close. I consider all play-off games as important qualification games, as it is the last chance for a country to qualify for the final tournament. My main analysis will include only the close qualifying games, but I will also test my hypothesis with all qualification games to see the difference.

3.1.2 Group stage

The final tournament usually takes place in June and July and starts with a group phase, of which I have obtained 263 results. Each participating country plays against three other national teams where after the two best teams in each group proceed to the next round. In general, the group stage consisted of eight countries before 1996 and since 1996, 16 countries participate. The consequence after one group game separately is not that large, as the final result after all group matches counts. The deciding group match can also differ. If a country wins the two first matches, it is already qualified for the next round. The same applies if a country loses the first two games. In other cases, which countries proceed to the next round usually depends on the third match. Therefore, there is not one game in this stage that can be considered as a final or elimination game.

3.1.3 Elimination stage

After the group stage, the elimination stage begins. This knockout phase consists of quarterfinals, semi finals and finals. Within these rounds, every game is decisive, as the loser of a match gets removed for the tournament immediately, and the winner proceeds to the next round. Except for the final, there is no direct gain involved with a win, while there is a direct negative consequence after losing a match. Combined with the concept of loss aversion explained in 2.5.1, I expect that the negative reaction after a loss will be stronger than a positive reaction after a win.

At the quarterfinals, only eight countries are left. There are 36 trading days after a quarterfinal was played, as not every tournament included quarterfinals. In the European Championship of 1976, the quarterfinals were no elimination games, as each quarterfinal was played twice, and I decided to drop these games from my sample.

The four national teams that win the quarterfinals proceed to the semi-finals, of which I have obtained 30 game results. These matches are elimination games too. The losing countries are eliminated from the tournament and the two winners proceed to the final. The two countries that lose play shortly before the final a match for the third and the fourth place. I do not include these third place-matches in my sample, as those countries are already eliminated from the tournament. The two winning countries play the final, where the winner is the European Champion. In total there are 17 trading days associated with a final.

In total, there are 1.951 match days of which 1.605 are qualification game results, 263 are group game results and there are 83 elimination game results.

3.2 Daily local returns

To collect financial data, I download the Total Return Index for each country of my sample from January 1st, 1973 to December 31st, 2012 from Datastream and use this index to compute the daily returns for each country. Unfortunately, I could not find financial data for every country that has participated in a European Championship in the past. This is either because this country does not exist anymore as a whole, or did not have a stock market (for example Czechoslovakia and USSR) or simply because the Total Return Index is not available. For many countries, I could only retrieve financial data later than 1973.

As there is no financial data available for each country of the United Kingdom separately, I have decided to link the financial data of the United Kingdom to the English national team, as 80% of the 64 million inhabitants of the UK lives in England. I dropped the observations for Cyprus when I use normalized instead of raw returns, because of inconsistencies in the estimated variances of this country's stock returns when normalizing these stock returns.

I also collect Europe Index returns, using the MSCI Price Index from Datastream. This index consists of large and mid equity market index data across 15 Developed Markets countries in Europe, countries that I include my sample as well. The UK, France, Switzerland and Germany capture the biggest part of this index. The MSCI Europe Index was launched in early 1986, and to be able to provide information earlier, they back-tested data, which means that they calculated how the index might have been during that time if the index would have existed [4].

For consistency, I aimed to use the Total Return Index here as well, but this index showed the same returns for one or two weeks in a row for some years. It is highly unlikely that the returns are exactly the same for a couple of days, which is probably due to this back-tested data approach. However, the Price Index changed almost on a daily basis, and therefore I considered this index more suitable to compute daily Europe index returns. Edmans, García and Norli (2007) use both the Price and Total Return Index too in their research.

Figures 1a and 1b show the returns of the 28 European countries in my sample. I divided my sample in two and used country codes to be able to give a clear (but general) overview of the country's stock returns. In Table A1 of the Appendix, I report the corresponding country for each code.

[4] https://www.msci.com/resources/factsheets/index_fact_sheet/msci-europe-index.pdf

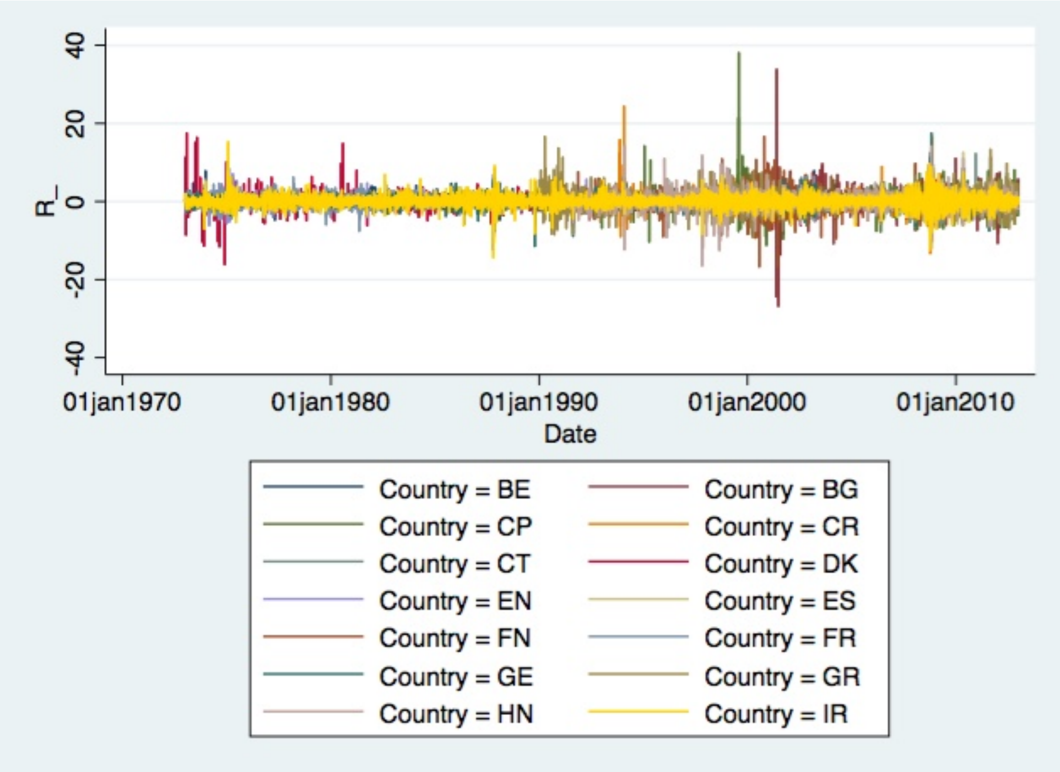

Figure 1a. Local market stock returns of European countries from 1973 to 2012

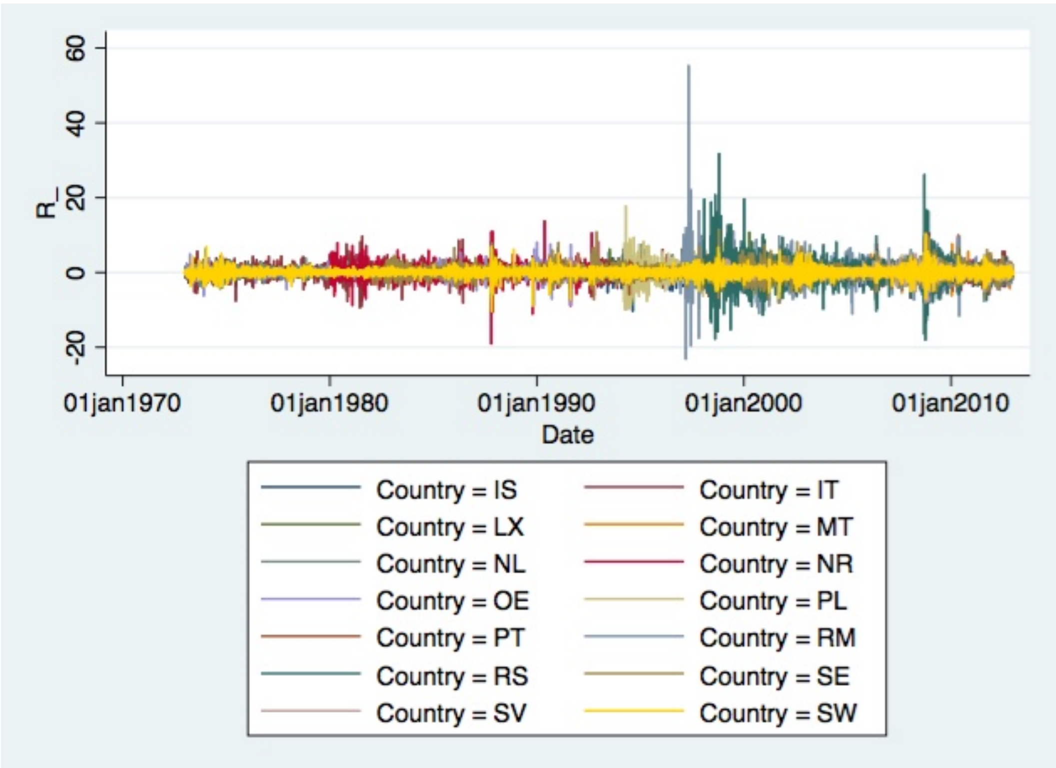

Figure 1b. Local market stock returns of European countries from 1973 to 2012

The daily returns in figure 1a vary a lot, and range from almost +40% to -25%. The graph shows high volatility on the Danish local stock (DK) market around 1973. From this year, Denmark experienced strong economic growth and the political structure changed a lot, which are possible reasons for the high volatility on this nation's stock market[5]. Moreover, around 2000 there is high variation in the daily returns of Cyprus and Bulgaria, varying from -10% to +35% and -25% to +40%, respectively. The graph in figure 1b shows high variation in the returns on the Romanian (RM) and Russian (RS) local stock markets. The daily returns of Romania vary from -22% to +55%, Russian daily returns vary from -18% to +30%.

The high volatility on some stock markets in figure 1a and 1b might be due to the fact that those countries were part of another nation first, and became independent countries around that time. It might have taken some time for the local stock markets to stabilize, with high volatility and varying returns as a consequence. In figure A1 in the Appendix, I plot the returns over time for each country separately.

3.3 Descriptive statistics

Table 1 provides descriptive statistics about the average returns on match days and non-match days. In my sample, there are 290.223 trading days without a match, and 1.951 trading days associated with a match. Of these 290.223 days, there are daily returns available for 195.954 days. The average return and standard deviation on these non-match days are 0,045% and 1,347 basis points, respectively. The average return on days after a match is 0,146%. There is financial data available for all match days, and this data also includes non-close qualifying games. In table A2 of the Appendix, I give an overview of the length of the time series, the average return and the amount of wins and losses per country.

On the 1.951 trading days, there are 981 wins, 564 losses and 406 draws. The amount of losses and wins is not the same because for some matches I could not

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http://web.archive.org/web/20070110120624/http://www.um.dk/Publikationer/UM/English/Denmark/kap6/6-18.asp find financial data for both countries on that day. I do not take draws into account in my data analysis but I include them in my sample to serve as a reference point. The average return after a draw is 0,065%, with a standard deviation of 1,58.

I use a t-test to test whether the average returns are different from zero. To do this, I generate variables called $R_{\mathit{stage}\mathrm{W}}$ and $R_{\mathit{stage}\mathrm{L}}$, where stage={qr, gs, el} refers to a game in a qualification, group or elimination stage, respectively. For example, the average return after a loss in an elimination game is called R_{elL}. After computing this variable, I run t-tests where I test the null hypotheses $R_{\mathit{stage}\mathrm{L}} = 0$ and $R_{\mathit{stage}\mathrm{W}} = 0$, unpaired and with unequal variances. Furthermore, I examine whether the differences between the returns after a win and loss are significant, by testing the null hypothesis $R_{\mathit{stage}\mathrm{W}} = R_{\mathit{stage}\mathrm{L}}$.

Table 1

Descriptive Statistics

This table reports the number of games for match and non-match days, including the average daily return and standard deviation. For match days, I calculate the mean return from Datastream's Total Return Index for the first trading day after a match. Besides all games, I distinguish between wins and losses in three subcategories, namely elimination games, group games and close qualifying games. My sample consists of 28 countries in total, covering a period from January 1st, 1973 to December 31st, 2012.

	No Games			Wins			Losses		
	Days	Mean	SD	Days	Mean	SD	Days	Mean	SD
No games	195.954	0,046	1,347						
All games				981	0,191	1,323	564	0,127	1,541
Elimination games				42	-0,103	1,563	38	-0,147	1,419
Group games				111	0,122	0,899	91	0,0320	1,327
Close qual. games				149	0,280	1,271	126	0,135	1,644

There are 981 trading days associated with a win the day before. These days have an average return of 0,191%, which is significantly different from zero (t-value= 4,53). The average return after a loss is 0,127%. This return is significantly different from zero at the 10% significance level (t-value= 1,96). The difference between both returns is not significant (t-value= 0,823), and so I can not reject the null hypothesis $R_W=R_L$.

Besides wins and losses in general, I look into three groups of matches: elimination games, group games and close qualifying games. Elimination games are matches during quarterfinals, semi-finals and finals, group games are matches during the group stage and close qualifying games are games considered to be important. In section 3.1.1.1, I elaborate more on how I select close and non-close qualification games.

The average return after an elimination game is negative for both wins and losses, -0,103% and -0,147% basis points, respectively. The negative return after losses is consistent with the view that negative soccer results influence stock prices in a similar way, as found by Edmans, García and Norli (2007). However, the average return after a loss is not significantly different from zero (t-value= -0,64) and the same applies for the return after a win (t-value = -0,43.) Also, the difference between both returns is not significant (t-value= 0,131).

When considering group games, there is a positive average return after both wins and losses: 0,122% and 0,032%, respectively. Both returns are indistinguishable from zero (the t-values are 1,43 and 0,23, respectively). Again, I can not reject the null hypothesis that the returns after a win and loss in the group stage are equal (t-value= 0,550).

Close qualifying games are followed by positive returns on the first trading day after the match. The average return after a win is 0,280%, which is significantly different from zero (t-value= 2,69). The return after a loss in this stage is 0,135%, indistinguishable from zero (t-value= 0,92). The difference between both returns is not different from zero either (t-value= 0,806).

For all trading days after a match, there is a positive average return after both wins and losses, except for elimination matches, where I find a negative average return after a win and loss. After performing a t-test, the returns after a win and loss in general are significantly different from zero, and also the average return after a win in a qualification stage is different from zero. However, I do not find a significant difference between the returns after a win and a loss. As the average return after a loss is not lower than the return after a win, there is no evidence for the loss effect.

4. Methodology

To measure the effect of European soccer results on stock prices, I look at the abnormal return of a country's local stock market on the first trading day after a match is played. Although some matches are played during daytime, I take the first trading day after the match to capture a full day.

4.1 Abnormal returns

The Efficient Market Hypothesis implies that stock prices only change when there is a change in the fundamental value of an asset. According to this framework, stock prices follow a random walk, which means they can not be predicted upfront. Moreover, if investors are rational, they make decisions that maximize their expected utility, and soccer results and other events that affect mood should not have an effect on stock prices.

Assuming that stock returns are unpredictable, there is not one model that is able to accurately explain returns. However, some factors have been identified to have an effect on stock market returns, for example prior local stock market returns, and Europe index returns, as it is likely that the returns of the Europe index also influence the returns on a local stock market. Moreover, some anomalies are known to partly explain stock prices, like the Monday effect and holidays.

I will first specify a model to explain stock returns, and estimate abnormal returns, which are defined as the residuals of this model. Abnormal returns are returns that can not be explained by the effects captured in a model, for example prior stock market returns. By definition, they have an expected value of zero.

I estimate the abnormal returns for each country using the following model, controlling for the Monday effect and other confounding effects:

$$R_{it} = \gamma_{0i} + \gamma_{1i} R_{it-1} + \gamma_{2i} R_{mt-1} + \gamma_{3i} R_{mt} + \gamma_{4i} R_{mt+1} + \gamma_{5i} D_t + \gamma_{6i} HD_t + \varepsilon_{it}, \qquad (1)$$

which is specified by Edmans, García and Norli (2007). For each country, I run a time series regression, using the reg command in Stata.

R_{it} is the local daily return on a stock market index for country i on time t. The local daily return is measured in a country's currency and is computed from the Total Return Index. R_{mt} is the daily return in euro on Datastream's MSCI Europe Price Index on day t. I use this Price Index to calculate the daily returns and convert the returns from US dollars into euro. R_{it-1} is included to control for first-order serial correlation. R_{mt-1} and R_{mt+1} represent the Europe Index one trading day before and one trading day after, to control for the fact that some local markets might be lagging the Europe index, while others might be leading it.

$D_t = \{D_{1t}, D_{2t}, D_{3t}, D_{4t}\}$ are dummy variables for Monday through Thursday. HD_t is a holiday variable, which is one if day t is a holiday and zero otherwise. I consider a day being a holiday if the return of a country on that day is zero, as it is highly unlikely that a country's return index is exactly zero on a regular day. With this approach, I select 2.576 holidays, controlling for the most important ones like New Year, Christmas and Easter.

Figure 2 shows the raw abnormal returns of the 28 countries in my sample that I use to estimate regression (2) and test my hypotheses. The corresponding country per code can be found in table A1 in the Appendix. Especially Romania (RM) has very high abnormal returns, up to about +40%. There is also a lot of variation in the abnormal returns of Russia (RS), and to less extent for returns of Cyprus (CP) and Bulgaria (BG). Similar as in figure 1, Denmark (DK) has high abnormal returns around 1973, which is probably due to the strong economic growth the country experienced those years. Also Poland (PL) and Czech Republic (CR) show a wide range of abnormal returns at the start of their time series.

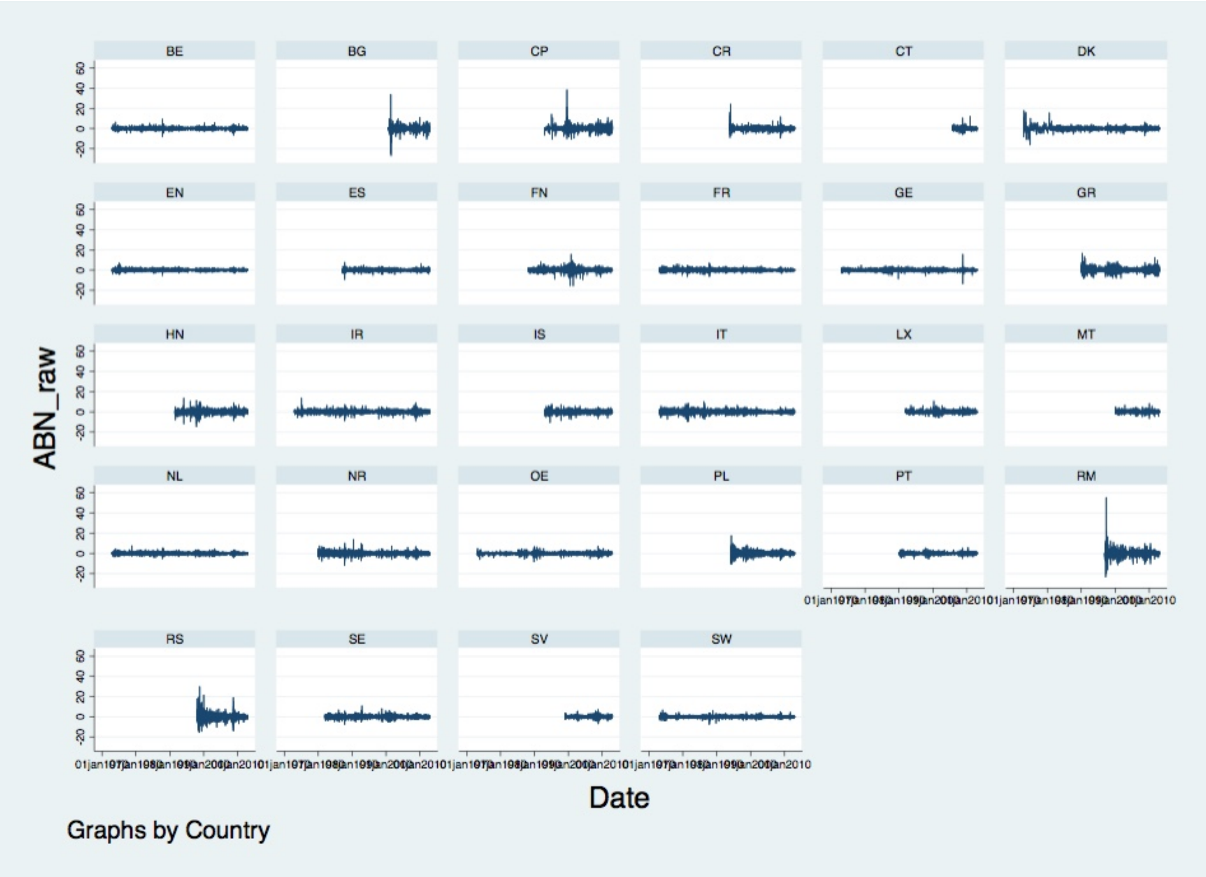

Figure 2. Raw abnormal returns per country

4.1.1 Normalized abnormal returns

One concern regarding this regression is the constant-volatility assumption, discussed by Edmans, García and Norli (2007). The volatility on a local stock market can vary over time, and causes the returns to be more extreme, which is shown in figures 1 and 2. In this case, it can happen that there is an abnormal return the first trading day after a match, caused by the high volatility on the stock market, but interpreted as evidence that soccer results affect stock prices.

To control for time-varying volatility, I apply a GARCH model to normalize the local market index returns. I compute the normalized returns as follows. First, I estimate regression (1) using a GARCH command in Stata to obtain the variances. Next, I divide the raw returns by their standard deviation and standardize these values to get the normalized returns. Finally, I run regression (1) again to obtain the normalized abnormal returns and test the effect of soccer results on stock returns.

When estimating the variances in Stata with the GARCH model, I noticed inconsistencies in the estimated variances of Cyprus' returns, so I decided to exclude Cyprus from my sample when using normalized abnormal returns.

Figure 3 displays the normalized abnormal returns, excluding Cyprus. They are somewhat similar to the abnormal returns in figure 2, but there are less extreme values because they are controlled for the volatility on a country's local stock market. Especially volatile stock markets as Romania (RM), Poland (PL) and Czech Republic (CR) show less extreme abnormal returns. For example, the abnormal returns for Romania vary now 'only' from +5% to -10% and also the other extreme returns have decreased.

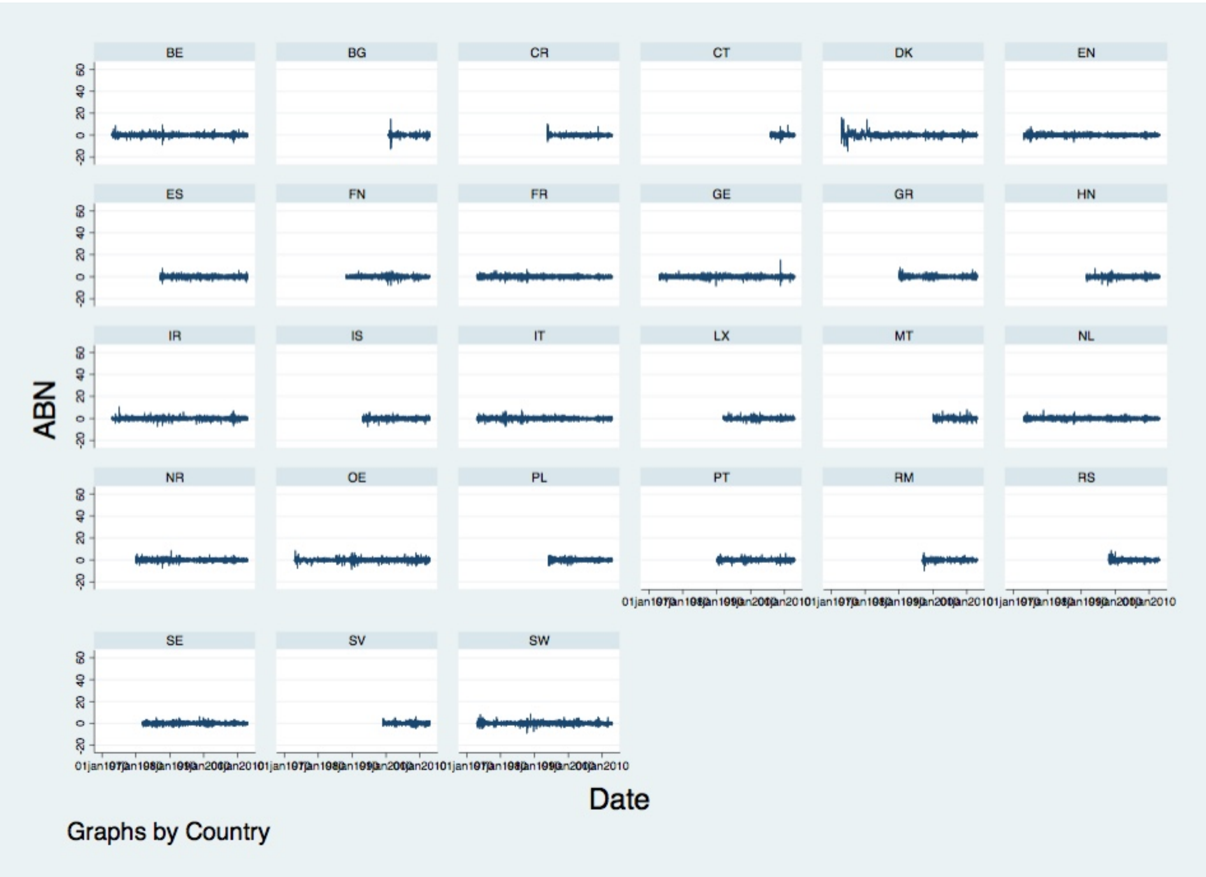

Figure 3. Normalized abnormal returns per country

4.2 International soccer results and stock returns

To test whether the outcomes of soccer matches influence stock returns, I estimate the following regression model

$$\hat{\varepsilon}_{it} = \beta_0 + \beta_W W_{it} + \beta_L L_{it} + u_{it}, \qquad (2)$$

where $\hat{\varepsilon}_{it}$ are the abnormal returns obtained from regression (1). W_{it}= {W_{it}, W_{it_qr} W_{it_gs} , W_{it_el}} are dummy variables for a win in general and wins in qualification, group and elimination games. A win dummy equals one if country i wins a game in subgroup g on day t, and zero otherwise. For example, W_{it_gs} is one if country i wins a match during the group stage where t is the first trading day after the match, and zero in all other cases. L_{it}= {L_{it}, L_{it_qr} L_{it_gs} , L_{it_el}} are similar dummy variables for losses, and equal one if a country loses a game in one of these rounds and zero otherwise. Note that the overall win and loss dummies include all games, also the non-important qualification games, causing the amount of games overall to be larger than the total of close qualifying, group and elimination games.

I will estimate this model twice; once with the overall win and loss dummy to capture the effect of a win and loss in general, and once with the subgroup dummies, to test the effect of a results in a specific round. Moreover, I will consider the effect of soccer results on stock returns using raw and normalized abnormal returns.

As I run regression (2) for all countries together, I set my dataset in Stata as panel data. This dataset is unbalanced, as not every country has data for all years. To perform an OLS regression, the Gauss-Markov conditions should hold, implying that among others, the error terms should be uncorrelated across time periods and the explanatory variables and the error term should be independent. However, as I observe several countries over multiple periods, it is unlikely to assume that the error terms from different time periods are uncorrelated. Therefore, the OLS is not BLUE (Best Linear Unbiased Estimator) and using General Least Squares (GSL) will lead to a more efficient estimator (Verbeek, 2012). In Stata, I will use the xtreg command to estimate my regression models. Within a GLS regression, there is choice between a random or fixed effects model. I will discuss both models and assess which one is more suitable for this research.

4.2.1 Fixed effects and random effects model

In an fixed effects model, each entity has an unobserved individual component that differs per observation. As Verbeek (2012) explains, it might be that these individual effects are correlated with explanatory variables, for example if whether a person is a male or female influences the age he or she starts working. As these time-invariant components are correlated with explanatory variables, they can not be treated as error terms. Rather, they are included in the intercept term, causing the intercept term to vary per entity, in this case countries.

A fixed effects model can be written like this

$$Y_{it}= X_{it}ß+\alpha_i+u_{it} \quad t=1,...,T, \; i=1,..., N, \qquad (3)$$

where X_{it} is an exogenous variable, ß is a coefficient estimate of a parameter of interest and α_i are the unobserved individual effects for each entity. In case of panel data on countries, it is common to use a fixed effects model.

Running a fixed effects model can be problematic if a time-invariant dummy variable is included in a model, because the effect of this dummy is already captured by α_i. For example, if a model includes a dummy to describe a person's gender, this effect of gender gets picked up by the intercept already, as the intercept varies over individual components. As a consequence, a fixed effects model can not estimate this dummy variable. I use time invariant dummies in my regression too, for example whether a country is a so-called soccer nation or not.

However, as the dependent variable of my model are abnormal returns, which are assumed to be zero, the intercept of my model is assumed to be zero too, and this might not be a problem.

On the other side, a random effects model is a model where the individual component is considered as random, and is included in the error term of the regression model (Verbeek, 2012).

A random effects model looks like this

$$Y_{it}= ß_0+X_{it}ß+\alpha_i+u_{it} \quad t=1,...,T, \; i=1,..., N, \qquad (4)$$

where X_{it} is an exogenous variable, ß is a coefficient estimate of a parameter of interest and $\alpha_i + u_{it}$ is treated as an error term consisting of an individual component and a remainder component. It is assumed that these two terms are independent of the explanatory variables (Verbeek, 2012). A random effects model is the default option in Stata.

In short, the main difference between a random and fixed effects model is whether the unknown individual components are correlated with the explanatory variables in a model or not.

The Hausman test is a common way to test which model to use. Under the null hypothesis, the coefficients estimated by a random and fixed effects model are equal. I first estimate regression (2) with the model I expect to be efficient, which is a random effects model in my case. Then, I perform the same regression using fixed effects and run a Hausman test. Rejecting the null hypothesis would mean that there is a significant difference between both models, while if I obtain insignificant results I could use both models. Performing the Hausman test results in a Chi^2-value of zero and a p-value of 1,00. I can not reject H0, indicating that I can use both models to analyze my data.

Although it is likely to assume that the individual effects in my model vary across countries, I will use a random effects model. To see whether there are considerable differences with a fixed effect model, I will also run my main regression using fixed effects. I will discuss the results in section 5.2.1.

4.2.2 Heteroskedasticity and autocorrelation

The Gauss-Markov conditions are commonly used to assess whether a model is a good estimator or not. According to the Gauss-Markov assumptions, the residuals of a model should meet the following requirements. The error terms should have an expected value of zero, they are uncorrelated over time and have a constant variance of σ^2. If the latter is not the case, there is heteroskedasticity, while if errors terms are correlated, this is referred to as autocorrelation.

To check whether my model satisfies these assumptions, I obtain the residuals of regression (2) using raw abnormal returns, which are shown in figure 4. Plotting these error terms suggests that there is heteroskedasticity, as the variances of the error terms are not constant. The error terms of Romania (RM) vary a lot, and also those of Denmark (DK), Bulgaria (BG) and Czech Republic (CR) have unequal variances. The error terms of most other countries vary as well, but to less extent. Only The Netherlands (NL), Switzerland (SW) and England (EN) display somewhat constant variances. One possible explanation for these heteroskedastic error terms is the volatility on stock markets, which causes stock returns to be more extreme and have larger variance.

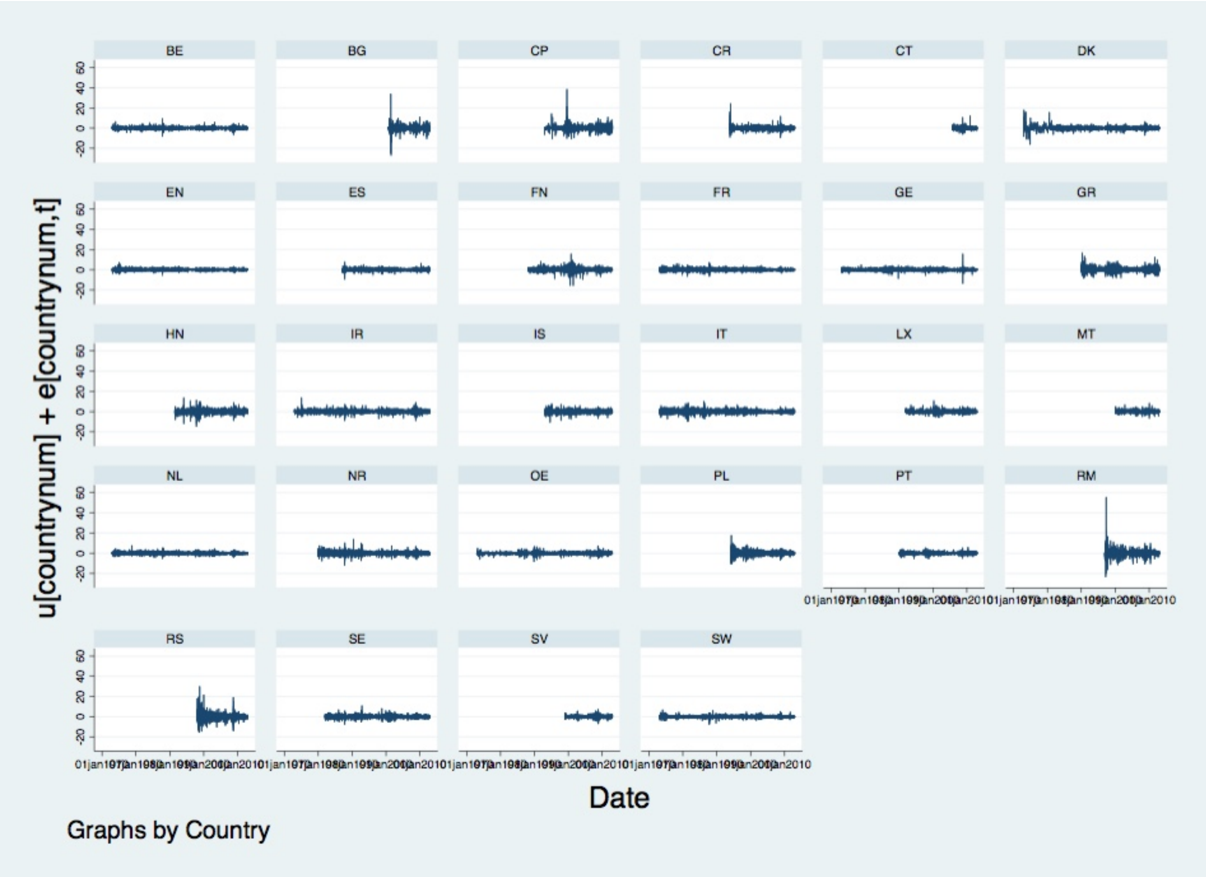

Figure 4. The error terms of regression (2) using raw abnormal returns

A way to deal with heteroskedasticity caused by a stock market's volatility is to normalize the stock returns. This procedure controls for the volatility on a stock market and attaches less weight to extreme returns, so these observations have less impact on the coefficient estimates of the model. In section 4.1.1, I explain how I normalize the stock returns of the 28 countries in my sample. The graphs in figure 5 show the residuals of regression (2) using normalized abnormal returns for each country. Compared to figure 4, the heteroskedasticity has decreased. Especially the error terms for Romania (RM), Bulgaria (BG) and Poland (PL) have become more constant. However, the variance in the residuals of Denmark (DK) has barely decreased.

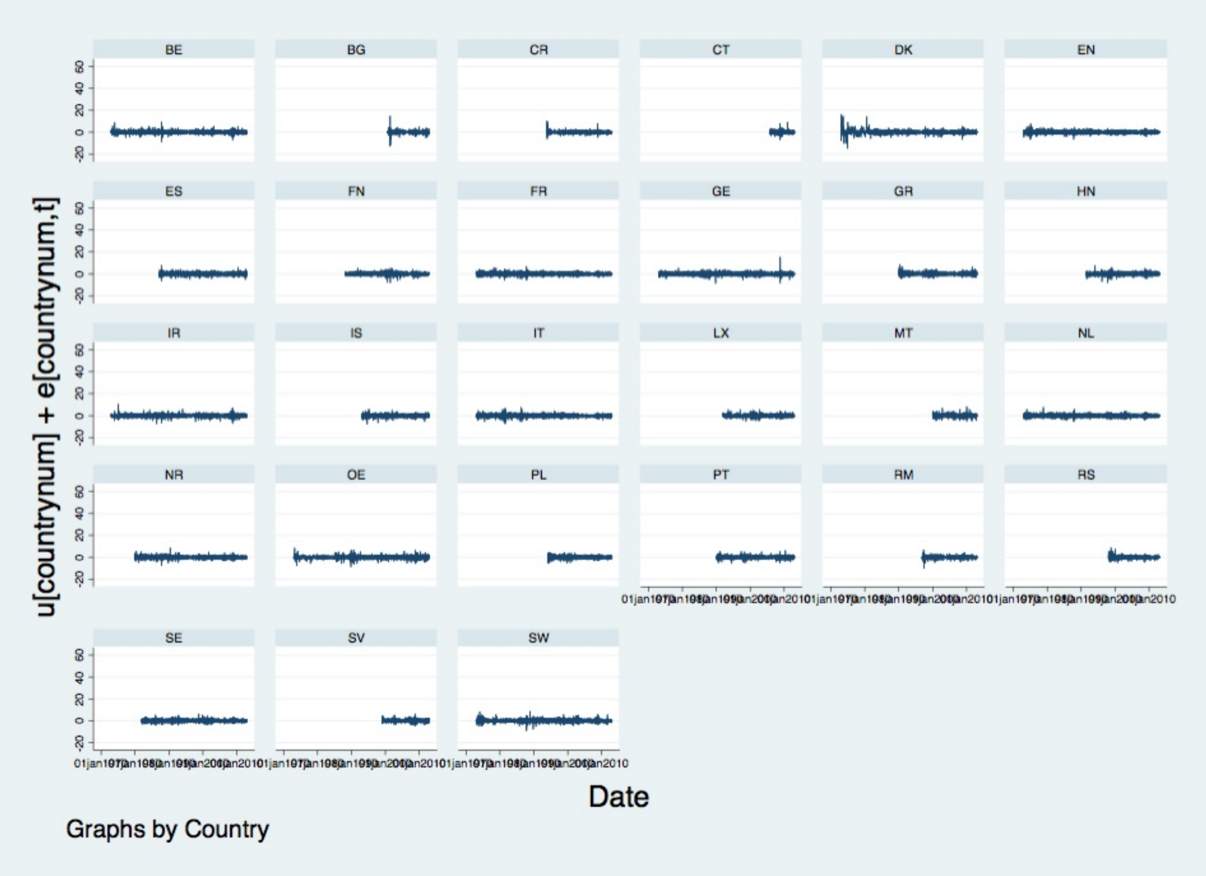

Figure 5. The error terms of regression (2) using normalized abnormal returns

Moreover, as I investigate countries over several time periods, it is reasonable to assume that error terms are correlated with error terms the day(s) before. To test whether there is autocorrelation, I use xtserial in Stata. Xtserial is a test developed by Wooldridge (2010) to test for autocorrelation in panel data, using a Wald test. A study by Drukker (2003) provides further evidence that this test has good size and power properties if the sample size is large enough. Under the null hypothesis, there is no serial correlation. Estimating model (2) with only the overall win and loss dummy using xtserial results in a significant F-statistic of 10,086. Consequently, I reject the null hypothesis that there is no first-order autocorrelation.

As Edmans, García and Norli (2007) explain, error terms can also be correlated across countries. This correlation can be caused by common shocks, like EU regulation, international political decisions or tensions between countries.

A way to deal with heteroskedasticity and correlation across countries is to run my regression using panel corrected standard errors (PCSE), as both Edmans, García and Norli (2007) and Hirshleifer & Shumway (2003) do. “PCSE assume that the errors terms u_{it} have a mean of zero and are, by default, heteroskedastic and contemporaneously correlated across panels" (Edmans, García & Norli, 2007).

Using PCSE brings additional assumptions to take into account, and the question is whether it will have a considerable impact on my results anyway. As I do not think that the benefits of this model outweigh the extra assumptions I have to take into account, I have decided to use the regular GLS panel regression, using the command xtreg.

Although, it seems reasonable to estimate model (2) with PCSE as a robustness check and consider the differences with my regular panel regression. I will elaborate on the results I obtain with PCSE in section 5.2.2.

4.2.3 Outliers

In this section, I investigate the sensitivity of my model to outliers. If an outlier occurs on the first trading day after a match, it can be interpreted as evidence that soccer results influence stock returns. Instead, it might be caused by another shock, like a crisis or political decision. It is difficult to decide whether a data point is an outlier, and therefore it is risky to drop extreme observations from a sample. I have decided not to remove extreme observations from my sample, but rather perform a robustness check to see if excluding the most extreme returns has an impact on my results. I will treat the highest and lowest 5% of my abnormal returns as outliers, and eliminate in this way the most extreme observations.

Figure 2 with raw abnormal returns shows many more extreme observations than figure 3 where normalized abnormal returns are used. By normalizing the returns, I already partly controlled for outliers, and therefore I expect that removing outliers for raw returns will have a larger effect on my results than removing observations for normalized returns.

To see if extreme abnormal returns on the first trading day after a match affect my results, I will perform two tests. First I will compare the mean returns after a match with and without outliers. Second, I will run regression (2) with my trimmed sample, to see if my results are different.

To examine whether outliers affect stock returns the first trading day after a match, I will only keep match days. I compute the average return for my untrimmed sample and do the same for my trimmed sample, after removing the 10% most extreme abnormal returns. I do this for both raw and normalized returns. Finally, I perform a t-test to test whether these returns are significantly different from zero or not.

Table 2

Mean Abnormal Returns after Match Days

This table reports the number of games and mean abnormal returns the first trading day after a match, using untrimmed and trimmed returns. The reported t-values are the results of a t-test, testing the null hypothesis that the mean return is equal to zero. I obtain the abnormal daily returns from the residuals from regression (1), using both raw and normalized returns. To calculate the trimmed means, I drop the highest and lowest 5% abnormal returns. My sample consists of 28 countries using raw abnormal returns and 27 countries when I use normalized abnormal returns. The sample period includes only match days, from September 5th, 1974 to July 2nd, 2012.

	Untrimmed			Trimmed		
	Days	Mean	t-values	Days	Mean	t-values
Raw abn. returns	1.545	0,033	1,22	1.391	0,011	0,67
Normalized abn. returns	1.507	0,004	0,22	1.357	-0,001	-0,07

The results are reported in table 2. After removing the so-called outliers, the daily raw abnormal return is on average 0,011%, and is not significantly different from zero. The untrimmed mean raw return is 0,033%, but is also indistinguishable from zero. As a consequence, I can not reject the null hypotheses that these abnormal returns are equal to zero. Considering the normalized returns, the untrimmed average return is close to the abnormal return with outliers, which makes sense as I already controlled for extreme results caused by stock market volatility here. The untrimmed mean return is 0,004 and is indistinguishable from zero (t-value= 0,22). Removing outliers result in a slightly negative abnormal return of -0,001 but this value is also not different from zero (t-value= -0,07)

As I expected, removing outliers has most impact on the raw abnormal returns, but this impact is minor, as both the untrimmed and trimmed abnormal return after a match are indistinguishable from zero. For both raw and normalized abnormal returns, I can not reject the null hypothesis that the average return after a match is equal to zero. These results make sense, as abnormal returns by definition have an expected value of zero.

Moreover, I run regression (2) again with trimmed returns to see whether these extreme observations have an impact on my results. I will discuss the results shortly in section 5.2.3.

4.2.4 Including all qualification games

In my main regression, I only include close qualification games. There are many qualification games played before each tournament and many of them are not likely to have an impact on investor mood, as the skills of both national teams differ a lot. To illustrate, I identify 382 qualification games as being close, and 1.205 games as non-close. To test to which extent the results differ if I would use all qualification games, I run regression (2) including also the non-important games. This increases my sample considerably, as 1.205 games are added to my sample. I expect the coefficient estimates of wins and losses during qualification games to become less strong, as now also non-important games are included. I discuss the results in section 5.2.4.

4.3 Top 7 soccer nations

Even though almost every country has a national soccer team, the importance of soccer varies across countries. Especially in countries with famous national competitions and with national teams performing well on international tournaments, the results of a Championship are likely to have a considerable impact on people's lives, and moods.

To test whether the effect of soccer results is stronger for so called 'soccer nations', I split my sample in two. I select seven countries where soccer is one of the most popular sports and run regression (2) for these countries, and the other 20 countries separately. Again, I will use a random effects model and apply normalized abnormal returns. I select The Netherlands, England, Spain, Portugal, Italy, France and Germany as soccer nations, based on the FIFA ranking and the most popular national soccer competitions. In total, the soccer nations won 433 matches and lost

123 times, while the 20 other nations won 537 matches and lost 416 times. I will probably lose some statistical power if I split my sample in two and perform regression (2) twice. However, I still consider both samples to be large enough.

Furthermore, I test whether the effect of soccer results on stock returns differs between soccer nations and the other countries, using interaction terms. I estimate the following model

$$\hat{\varepsilon}_{it} = \beta_0 + \beta_1 soccernation + \beta_2 W_{it} + \beta_3 L_{it} + \beta_4 * soccernation * W_{it} + \beta_5 * soccernation * L_{it} + u_{it}, \quad (4)$$

where $\hat{\varepsilon}_{it}$ are the normalized abnormal returns obtained from regression (1). 'Soccer nation' is a dummy variable that equals one if a country is considered as a soccer nation and zero otherwise. W_{it} is a dummy variable that equals one if country i wins a match on day t, and zero otherwise. L_{it} is a dummy variable for losses, and is defined similar. I include two interaction terms, 'soccer nation' and W_{it} to test whether the effect for soccer nations and non-soccer nations is different after a win and 'soccer nation' and L_{it} to test the same after a loss. For this regression, I only use the general win and loss dummy, and do not take different stages into account.

Note that in fact, it does not matter whether to use an interaction term or estimate the model twice, once for the soccer nations and once for the other countries. Subtracting the two coefficients from the separate regressions will result in the coefficient of the interaction term. I decided to use the latter to easily test whether there is a significant difference. The results of this regression can be found in section 5.3.

4.4 Home countries

During every European Championship, there are one or two countries that organize the tournament. It is possible that match outcomes of a hosting country have a larger impact on investor mood, resulting in a stronger effect on stock returns. The fans of the home country experience the tournament more intense, as the whole nation is under the spell of this event and supporters are able to attend a match of their national team.

The effect of soccer results on stock returns can also be stronger because of economic reasons, as there are large economic benefits tied to hosting an international tournament. For instance increased tourism, more employment, and the development of infrastructure can boost the economy of a country before, during and even after the event. Note that if investors in a hosting country react more strongly to soccer results because of economic activity, they behave rationally. Nevertheless, these factors can affect the relationship between soccer results and stock returns.

The country that hosts a European Championship is automatically qualified for the final tournament. For some countries, this is the only opportunity to participate in the final tournament. For example, Poland organized the European Championship in 2012, which was the only time the country participated in the group games.

In total, there are 11 home countries, divided over nine European Championships, as two tournaments were played in two countries. There is no home country in my sample for the European Cup of 1976, as it was hosted by Yugoslavia, and there was no financial data available on Datastream for this country. There are 43 trading days after these countries played a game while they hosted the tournament. The home countries won 23 times and lost 13 matches. The eight other results are draws.

To test whether the effect of soccer results on local stock returns is stronger for hosting countries, I estimate the following model

$$\hat{\varepsilon}_{it} = \beta_0 + \beta_1 home + \beta_2 W_{it} + \beta_3 L_{it} + \beta_4 {*}home{*}W_{it} + \beta_5 {*}home{*}L_{it} + u_{it}, \quad (5)$$

where $\hat{\varepsilon}_{it}$ are the normalized abnormal returns obtained from regression (1). ‘Home’ is a dummy variable that equals one if a country is a host during a match and zero otherwise. W_{it} is a dummy variable that equals one if country i wins a match on day t, and zero otherwise. L_{it} is a dummy variable for losses, and is defined similar. I include two interaction terms, ‘home’ and W_{it} to test whether the effect for hosting and non-hosting countries is different after a win and ‘home’ and L_{it} to test the same after a loss. For this regression, I only use the general win and loss dummy, and do not take different stages into account.

If the effect of soccer results on stock prices is stronger for hosting countries, then the interaction effect should be significantly positive for wins and/or losses. Section 5.4 discusses the results of this analysis.

4.5 Before and after the euro

An assumption that is made about investors is that they mostly invest in domestic stocks. This phenomenon is called the home bias and is an important statement for the effect of investor mood on stock prices. If investors invest in all kind of stocks over the world, then the effect of their mood on asset pricing will be divided over foreign stock markets, and will not be solely reflected on their country's local stock market.

However, studies by Giofré (2008) and Schoenmaker and Bosch (2008) show that the home bias in Europe has decreased over the last years, due to the entrance of the euro in 2002. Because many European countries use the same currency now, it has become less costly and risky for investors to invest in other euro-countries. As a consequence, investors spread their investments over diverse euro-countries, and their behavior due to change in their mood is divided over multiple stock markets.

It is interesting to examine the effect of soccer results before and after the entrance of the euro, for euro and non-euro countries. If indeed, the effect of soccer results on stock prices is smaller for euro-countries after 2002, this does not mean that investor mood is not influenced by soccer results anymore. Rather, it indicates that the effect has become less visible because it is spread over multiple countries. Testing this difference will be an indirect test of the home bias.

My sample consists of 14 euro countries and 13 non-euro countries. There are 1.101 soccer results for euro countries, and 804 results for non-euro countries. Euro countries won 567 times and lost 316 games, while non-euro countries won 403 and lost 223 matches. The total amount of soccer results also includes draws, but I do not include these in my analysis. Rather, they serve as a reference point.

I estimate the effect before and after the euro for euro and non-euro countries with the following model

$$\hat{\varepsilon}_{it} = \beta_0 + \beta_1 \text{after euro} + \beta_2 W_{it} + \beta_3 L_{it} + \beta_4 {*}\text{after euro}{*}W_{it} + \beta_5 {*}\text{after euro}{*}L_{it} + u_{it}, \quad (6)$$

where $\hat{\varepsilon}_{it}$ are normalized abnormal returns obtained from regression (1). 'After euro' is a dummy variable that is one if the match was played in 2002 or later, and zero otherwise. W_{it} is a dummy variable that equals one if country i wins a match on day t, and zero otherwise. L_{it} is a dummy variable for losses, and is defined similar. I include two interaction terms, 'after euro' and W_{it} to test whether the effect before and after the euro is different after a win and 'after euro' and L_{it} to test the same after a loss. For this regression, I only use the general win and loss dummy, and do not take different stages into account. I run this regression twice, once with euro countries and once with non-euro countries.

Obviously, the currency for non-euro countries has remained the same, but they serve as a reference point and to control for other factors that could have an influence on stock returns. Therefore, I do not expect to find any significant results for these countries. Moreover, this way of analyzing will decrease the power of my regression as I split my sample in two, so that I have fewer observations per regression. Second, I turn a continuous variable describing the date of the match into a dummy variable 'after euro'. Creating this variable allows me to compare the effects before and after the euro, but will also decrease the statistical power of my test. Still, I consider my sample to be large enough.

Considering euro countries, a positive interaction effect of a loss and 'after euro' indicates that the effect was stronger for losses after 2002 than before 2002. This would be consistent which the idea that investors also invest in foreign stocks now, so that the effect of their mood after a lost game is not solely concentrated in one stock market anymore and therefore less visible. The results of this analysis are reported and discussed in section 5.5.

4.6 Probabilities and stock reactions

If investors are rational, soccer results should not influence their behavior on the stock market. However, investors can react positively (negatively) after a win (loss) and still be perfectly rational, because of the economic consequences after a match, assuming that soccer results have an impact on economic activity. Negative consequences after a loss are for example lower sales of merchandise and advertising, while a win can give the sales of soccer merchandise a boost. Moreover, due to mood changes, there can be a reduction in consumer expenditures after a loss, and an increase after a win.

If the Efficient Market Hypothesis holds, investors update their expectations about match outcomes immediately. So, if they expected a loss and this loss occurs, there should be no stock reaction after this soccer result as they incorporated the expected consequences of this loss already. However, if an unexpected win or loss occurs, investors have to update their beliefs and absorb this new information. In this way, it is possible to observe a stock reaction after a soccer match, and investors are still rational.

I use match outcome probabilities to determine whether a soccer result was expected or not. To test whether there is a stronger stock reaction after an unexpected soccer result, I regress the normalized abnormal returns obtained in regression (1) on a win dummy and the probability to win a match.

To compute probabilities, I follow the approach by Edmans, García and Norli (2007) and use ELO ratings and the following formulas

$$\text{P(Home-team wins)} = \frac{1}{10^{-(E_H + 100 - E_A)/400} + 1} \qquad (7)$$

if it concerns a qualification game, and

$$\text{P(Home-team wins)} = \frac{1}{10^{-(E_H - E_A)/400} + 1} \qquad (8)$$

if it concerns a game in the final tournament.

E_H is the ELO rating of the home team, and E_A the ELO rating of the away team. During the tournament, no team has a home field advantage anymore, so I use the team that is listed first as the home team. I apply these formulas to all matches in my sample. Logically, I calculate the probability of the away team winning the match as one minus the probability of a win of the home team.

Edmans, García and Norli (2007) report a correlation of 0,929 between ELO ratings and obtained betting odds data, and Hausch and Ziemba (1995) show that betting odds are closely related to objective probabilities, implying that the probabilities calculated from ELO ratings serve well as an indicator for expected game results.

Unlike the study by Edmans, García and Norli (2007), I include all qualification games instead of only the close ones. I do this because both probabilities and close-qualifying games are related to the ELO ranking. If a qualification game is considered as close, this means that the difference between the ELO ratings is rather small and this also influences the probability of a win. In total, I have computed 1.403 outcome probabilities. I do not have probabilities for each game, as I could not calculate them if the ELO rating of one of the two countries in a match misses.

I estimate the effect of match outcome probabilities on stock returns with the following model

$$\hat{\varepsilon}_{it} = \alpha_0 + \alpha_1 W_{it} + \alpha_2 P_{it} + u_{it}, \quad (9)$$

where $\hat{\varepsilon}_{it}$ are normalized abnormal returns obtained from regression (1). W_{it}= {W_{it}, W_{it_qr} W_{it_gs} , W_{it_el}} are dummy variables for a win in general and wins in qualification, group and elimination games and equal one if country i wins a match in group g on day t, and zero if it loses a match. Consequently, my sample consists of only match days. P_{it} is the probability that country i wins a match on day t. Again, I estimate this model twice, once with the overall win dummy, and once with win dummies for qualification, group and elimination games. To be able to compare my results with earlier findings, I standardize the probability variable to have a mean of zero and standard deviation of one (Edmans, García & Norli, 2007). If the effect after an unexpected win or loss is larger than after an expected outcome, the coefficient of the probability variable should be significantly different from zero.

5. Results

This section contains the results of my paper. First, I will report the main results of my research and some robustness checks to test whether my results hold under different assumptions. Then, I discuss the results for specific countries and time periods and test whether there is a relationship between match outcome probabilities and stock returns.

5.1 International soccer results and stock returns

Table 3 reports the results of the main regression of this paper. Panel A shows the effect of international soccer results on countries' local stock markets using abnormal raw returns. In Panel B, the normalized returns are used to control for time-varying volatility on stock markets. In both tables, I apply a random effects GSL regression, which assumes that the individual components are random across countries and included in the error term. I run the regression for both raw and normalized abnormal returns twice, once to capture the effect of a loss and win in general and once for wins and losses in three subgroups. Moreover, I report the amount of match results per subcategory.

The R^2 of both models is (close to) zero, indicating that these models explain (almost) nothing of the variation in my dependent variable, abnormal returns. These low values make sense though, as these abnormal returns are the residuals of regression (1), which means that this model could not explain these returns in the first place. It is therefore unlikely that relatively few soccer results are able to explain thousands of abnormal returns, as there are many abnormal returns and relatively few are associated with a match. Moreover, I can not reject the null hypothesis that the joint coefficients of the model are zero.

Table 3

Abnormal Daily Returns after International Soccer Results

I estimate the following model, using a GLS estimator and random effects model

$$\hat{\varepsilon}_{it} = \beta_0 + \beta_W W_{it} + \beta_L L_{it} + u_{it},$$

where $\hat{\varepsilon}_{it}$ are the normalized abnormal returns obtained from regression (1). W_{it} consists of dummy variables for wins overall and in close qualification, group and elimination games, called W_{it}, W_{it_qr} W_{it_gs} and W_{it_el}, respectively, and is one if country i wins a game in stage g on day t, and zero otherwise. L_{it} are similar dummy variables for losses, called L_{it}, L_{it_qr} L_{it_gs} and L_{it_el}. I will estimate this model once with the overall win and loss dummy to capture the effect of a win and loss in general, and once including subgroups. My sample consists of 28 countries using raw abnormal returns and 27 countries when I use normalized abnormal returns. The sample period is from January 1st, 1973 to December 31st, 2012.

	Wins			Losses		
	Days	$ß_W$	z-values	Days	$ß_L$	z-values
Panel A: Abnormal Raw Returns						
All games	981	0,039	1,05	564	0,024	0,49
Elimination games	42	-0,033	-0,18	38	-0,140	-0,75
Group games	111	0,140	1,28	91	0,086	0,71
Close qual. games	149	0,103	1,09	126	0,030	0,29
Panel B: Abnormal Normalized Returns						
All games	970	0,005	0,20	539	0,002	0,06
Elimination games	42	-0,040	-0,32	38	-0,022	-0,17
Group games	111	0,084	1,09	91	0,021	0,25
Close qual. games	146	0,046	0,69	125	0,019	0,26

In Panel A, I first test the effect of a win and loss overall. The number of total match results is larger than the sum of the match results in the subgroups, because all wins and losses also include non-close qualification games, which are not included in the subgroup analysis. The coefficient estimate after an overall win is 0,039, which can be interpreted as follows: if a match is won, the return on a local stock the first trading day after the match is 0,039% higher than average. However, the coefficient is indistinguishable from zero (z-value= 1,05). The coefficient of $ß_L$ is 0,092, also not significant (z-value= 0,49), indicating that a lost match does not affect stock prices. Consequently, I can not reject the null hypothesis $ß_L$=0 and I do not find evidence for the loss effect.

Besides the win and loss dummy for all games, I also take into account wins and losses during specific stages of the tournament, namely qualification, group and elimination rounds. Elimination rounds include quarterfinals, semi-finals and finals.

An elimination game is different from other games in the sense that there is a direct consequence after a match outcome, especially after a loss. If a country loses for example a semi-final, it gets removed from the tournament immediately. Therefore, it is possible that the negative effect after a loss is larger than the positive effect after a win. Moreover, according to loss aversion, losses loom larger than gains, and this can increase this effect. However, the coefficient estimate of a loss is insignificant (-0,140), indicating that a lost elimination game does not have an effect. The coefficient of a win is -0,033, insignificant either.

Group games are considered as non-elimination games, as there is no direct consequence tied to one win or loss. Rather, the final result after all group matches counts. The results after a win or loss are both insignificant, 0,140 and 0,086 respectively, implying that match results from group games do not impact stock returns. Close-qualification games are non-elimination games too. The coefficient of a won close qualification game is 0,103, but not significant (z-value= 1,09). Moreover, I do not find an effect after a loss in this stage either. The coefficient after a loss in the qualification stage is 0,030, indistinguishable from zero (z-value= 0,29).

Similar to Edmans, García & Norli (2007), I do not find a significant effect after a win. However, I do not find evidence that lost soccer matches affect stock returns either.

5.1.1 Using normalized abnormal returns

In Panel B, I run the same regression but apply a GARCH model to normalize the returns. This process is further explained in section 4.1.1. The GARCH model controls for the time-varying volatility on local stock markets, and gives less weight to observations in volatile stock markets. Therefore, the more extreme returns in these volatile markets will have less impact on the coefficient estimates. The number of games is lower here (970 wins and 539 losses), as I dropped Cyprus because of inconsistencies in the estimate variances of the returns. The R^2 of both models is equal to the ones in panel A. According to the two reported F statistics, I can not reject the null hypothesis that the joint coefficients are zero.

The effect size of the coefficients in Panel B can be interpreted as follows. First note that the coefficient of 0,002 of the overall loss dummy indicates that B_L is 0,002 standard deviations above its mean. Following Edmans, García & Norli (2007), I multiply this with the average volatility on a stock market of 1,347, which gives an abnormal raw return of 0,003. For a win, this is 0,005 multiplied by 1,347, which results in an abnormal raw return of 0,007. The results after a win and loss are not significant, indicating that these match results do not impact stock returns. Regarding the game subgroups, the directions of the coefficients are similar to the results in panel A. Except for the z-value of a won elimination game, the z-values are closer to zero than in panel A. Again; I do not find an effect after a win or a loss.

According to these results, I reject Hypothesis 1. I do not find evidence that European soccer results of a national soccer team have an effect on a country's local stock market the first trading day after a match, nor do I find evidence that this effect is stronger for losses than for wins.

Moreover, I also reject Hypothesis 2. I do not find a stronger effect for elimination games than for and non-elimination games. The coefficients of both groups are insignificant, indicating that the match results of these groups both do not influence stock returns.

5.2 Robustness tests

In this section, I will test whether my results in section 5.1 are robust to methodological changes. As a robustness test, I will first use a fixed effects model instead of a random effects model. Then I will estimate my regression with panel corrected standard errors (PCSE) instead of the regular panel regression. I will use trimmed outliers to see whether my results are driven by extreme returns and I will finish with a regression model where I include all qualification games, instead of only the important ones. I will discuss the results of each test shortly and compare them with my main results. I have included the results in the Appendix, in tables A3 to A6.

5.2.1 Fixed effects model

According to the Hausman test, I can not reject the null hypothesis that the coefficients using a random or fixed effects model are the same. Therefore, when I estimate my model with fixed effects, the results should be similar. Table A3 of the Appendix shows the results of running regression (2) with a fixed effects model.

In panel A, raw abnormal returns are used. Both the coefficient estimates and the z-values are exactly the same, implying that it does not matter whether I use a random effects or a fixed effects model. Panel B shows the results of a fixed effects model with normalized returns, and the results are again equal, indicating that my results also hold using a fixed effects model.

5.2.2 Panel corrected standard errors

As discussed in section 4.2.2, it is probable that the error terms of regression (2) are heteroskedastic and correlated across countries. One way to treat these error terms is to use panel corrected standard errors (PCSE). Panel corrected standard errors assume that the error terms are by default heteroskedastic and contemporaneously correlated across panels, in this study countries.

In Table A4 of the Appendix, I report the effect of soccer results on stock returns, using PCSE. Panel A describes the results using raw abnormal returns. The coefficient estimates are exactly the same as in Panel A of table 3, but the z-values are slightly different. This makes sense as PCSE correct the standard error of the coefficient estimate but not the magnitude of the coefficient itself. For wins and losses overall, the z-value has decreased to 0,79 and 0,43, respectively. The z-values of the other coefficients are slightly different as well; they have decreased using panel corrected standard errors, except for wins and losses in elimination games. All results remain insignificant.

Panel B shows the results for the same regression, using normalized abnormal returns. In all cases, the z-values are closer to zero using PCSE, except for results in the elimination stage. Those z-values have become more negative, but are still insignificant.

To conclude, using panel corrected standard errors results in the same coefficient estimates and in most of the cases slightly smaller z-values. Overall, the differences with my results in table 3 are only minor, and thus my results appear to be robust to PCSE.

5.2.3 Trimmed outliers

To test whether my results are driven by extreme observations, I remove the highest 5% and lowest 5% abnormal returns from my sample and run regression (2) again with raw and normalized returns. The results are reported in table A5 of the Appendix. Before trimming my sample, the normalized returns have less extreme observations than the raw returns, because these are already controlled for time-varying volatility on local stock markets. Therefore, I expect that removing outliers will have less impact on the normalized returns than on raw returns.

Panel A shows the results of regression (2) with trimmed raw abnormal returns. Overall, the coefficient estimates are closer to zero than the ones in table 3. For example, the coefficient after an overall loss is now -0,007, while it was 0,024 and also the coefficient estimate of the win dummy is smaller. The coefficient estimates of the game subgroups have also changed, but all remain insignificant, implying that after removing the most extreme returns, there is no relationship between soccer results and stock reactions.

Panel B reports the results using normalized abnormal returns. The coefficient of an overall win has remained the same, but the z-value has increased to 0,26. The coefficient of a loss has become negative, still insignificantly different from zero. The coefficient estimates after a loss in a group and close qualification game are negative now, while the coefficient of a win in an elimination game has become positive, 0,073. Even though some coefficients have an opposite sign, none of them is significant.

I expected that this procedure would have a larger effect on raw abnormal returns than on normalized abnormal returns, but this (minor) effect seems to be somewhat similar. To conclude, trimming outliers changes the size and the sign of the coefficient estimates somewhat, but the results remain insignificant.

5.2.4. Including all qualification games

The results displayed in table 3 only include close qualifying games, which are games that are more likely to be considered as important and influence investor mood. Following Edmans, García & Norli (2007), I distinguish between important and non-important qualifying games based on the ELO rating of both opponents during a match. If the difference between the ELO ratings of two opponents during a qualification game is less than 125 points (after adding 100 points to the team with the home field advantage), this game is considered as close. In section 3.1.1.1, I elaborate more on this process.

Table A6 of the Appendix reports the results of regression (2), including all qualification games, using normalized returns and a random effects model. As now also the non-important qualification games are included, it seems reasonable to expect that the effect on stock prices becomes less strong, especially for qualification games. Including all qualification games expands my sample to 806 wins and 404 losses during qualification games.

After adding non-close qualification games to my analysis, the coefficients of the win and loss dummy of qualification games have become smaller, -0,001 and 0,002, respectively, and are both insignificant. The z-value of the win coefficient is 0,03, while it was 0,69 and the z-value of the loss coefficient has become 0,05, while it was 0,26 when I only included close games. The coefficient estimates of win and losses in other subgroups have remained the same.

My results remain similar after including all qualification games. The coefficient estimates of the win and loss dummy in qualification games have become smaller, but I did not find an effect with close qualification games, and it was unlikely that my results would have become significant when I included all qualification games.

To conclude this section, performing these robustness checks changes the magnitude and the sign of the coefficient estimates somewhat, but overall, my results remained the same, indicating that they are robust to methodological changes. I do not find evidence that the results I find in table 3 are driven by the assumptions and regression model I apply to analyze my data.

5.3 Top 7 soccer nations

In some European countries, soccer is of greater importance than in other countries. It could be that the insignificant results I report in section 5.1 are driven by countries where football is less important. To test whether this is the case, I identify seven countries as top soccer nations and run regression (2) separately for these and the 20 other countries to see if there is a relationship between soccer results and stock returns when only examining soccer countries. Moreover, I will investigate whether the effect of soccer results on stock returns is different for soccer nations and non-soccer nations.

Table 4 first shows the results for the Top 7 Soccer Nations, followed by the results for the other 20 countries in Panel B. My sample consists of 697 observations for soccer nations, and 1.210 results for the other countries.

The seven soccer nations have won 433 matches and lost only 123 games, which supports my argument that these nations perform well on international tournaments. Most trading days were after group matches. There are only 44 match results of close qualification games, indicating that most of the qualification games these soccer nations played were probably considered as non-close as their national teams were expected to be of much better quality than the other team.

Table 4

Abnormal Daily Returns after International Soccer

Results for Top 7 Soccer Nations

I estimate the following model, using a GLS estimator and random effects model

$$\hat{\varepsilon}_{it} = \beta_0 + \beta_W W_{it} + \beta_L L_{it} + u_{it},$$

where $\hat{\varepsilon}_{it}$ are the normalized abnormal returns obtained from regression (1). W_{it} consists of dummy variables for overall wins and and wins in qualification, group and elimination games, called W_{it}, W_{it_qr} W_{it_gs} and W_{it_el}, respectively. L_{it} are similar dummy variables for losses, called L_{it}, L_{it_qr} L_{it_gs} and L_{it_el} and is one if a country loses a game in one of these rounds and zero otherwise. I run this regression for soccer nations and non-soccer nations separately. I will estimate this model once with the overall win and loss dummy to capture the effect of a win and loss in general, and once including subgroups. My sample consists of 7 soccer nations and 20 non-soccer nations. The sample period is from January 1st, 1973 to December 31st, 2012.

	Wins			Losses		
	Days	$ß_W$	z-values	Days	$ß_L$	z-values
	Panel A: Top 7 Soccer Nations					
All games	433	-0,010	-0,27	123	0,006	0,08
Elimination games	33	-0,039	-0,28	27	0,046	0,30
Group games	76	0,068	0,73	34	0,015	0,10
Close qual. games	27	-0,206	-1,31	17	-0,198	-1,00
	Panel B: Other countries					
All games	537	0,018	0,51	416	0,001	0,02
Elimination games	9	-0,042	-0,16	11	-0,192	-0,78
Group games	35	0,120	0,87	57	0,025	0,23
Close qual. games	119	0,104	1,39	108	0,053	0,67

Using normalized abnormal returns, I do not find an effect after wins or losses of these top soccer nations. The coefficient estimate after a win is -0,010 with a z-value of -0,27, and the loss dummy has a coefficient estimate of 0,006.

Considering game subgroups, I do not find an effect either. There are 33 trading days after a won elimination game, and 27 trading days after a loss in this stage. The coefficients of the win and loss dummy for this round are -0,039 and 0,046, respectively. The results for wins and losses in the group stage are also insignificant ($ß_W$= 0,068 and $ß_L$= 0,015) and the same applies to wins and losses in close qualification games. The coefficient of the win dummy of this stage is 0,104, and the loss dummy has a coefficient estimate of -0,198. Most trading days were after group matches.

The results for the other 20 countries are displayed in Panel B. The matches of these countries result in 537 wins and 416 losses, most of them close qualification games.

Similar to Panel A, I do not find evidence that soccer results of countries in this sample affect stock prices. The coefficient estimate after a win is 0,018 with a z-value of 0,51 and the loss coefficient has value of 0,001, with a z-value of 0,02. Most of the results of these countries are close qualification games, indicating that these countries often did not participate in the group stage or higher. The coefficient estimates for wins and losses in the qualification stage are 0,104 and 0,053, but these values are insignificantly different from zero. The remainder of the results is insignificant too, indicating that the match results of these countries do not have an effect on stock prices.

After considering the effect of soccer results on stock returns for soccer nations and non-soccer nations separately, I will test whether the difference between these two effects is significant, looking at the interaction effect between whether a country is a soccer nation or not, and the effect of a win and loss. If there is a positive (negative) interaction effect, this would indicate that the effect is stronger (weaker) for soccer nations than for the other 20 countries.

The results are reported in table 5. The interaction coefficient of a win and a soccer nation is negative, -0,029 but insignificantly different from zero (z-value= -0,54). This indicates that the effect of a win on stock prices is not stronger for soccer nations than other countries. Note that this value of -0,029 is the result of subtracting the two coefficient estimates for wins of soccer nations (-0,010) and non-soccer nations (0,018) in table 4. The interaction term for losses is 0,005, which indicates that there is no difference between the effect of a loss by a soccer nation and a non-soccer nation.

Table 5

Difference Between The Effect of Soccer Results on Stock Returns for Soccer Nations and Other Countries

I estimate the following model, including two interaction terms, using a GLS estimator and random effects model

$$\hat{\varepsilon}_{it} = \beta_0 + \beta_1 soccernation + \beta_2 W_{it} + \beta_3 L_{it} +$$
$$\beta_4 * soccernation * W_{it} + \beta_5 * soccernation * L_{it} + u_{it},$$

where $\hat{\varepsilon}_{it}$ are the normalized abnormal returns obtained from regression (1). Soccer nation' is a dummy variable that is one if a country is considered as a soccer nation and zero otherwise. W_{it} is a dummy variable that is one if country i wins a match on day t and zero otherwise. L_{it} is a loss dummy and is defined similarly. The 7 soccer nations in my sample are The Netherlands, Italy, France, England, Portugal, Germany and Spain. The sample period is from January 1st, 1973 to December 31st, 2012.

	Days	ß	z-values
Soccer nation	697	0,000	0,04
W_{it}	433	0,018	0,51
Soccer nation* W_{it}		-0,029	-0,54
L_{it}	123	0,001	0,02
Soccer nation* L_{it}		0,005	0,06

I do not find an effect for soccer nations, indicating that international soccer results do not have a significant effect on local markets' stock prices, even among countries where soccer is of considerable importance. My results are also insignificant for the other 20 countries. Moreover, I find no evidence that the effect of international soccer results on stock prices is stronger for top soccer nations than for 20 other European countries.

5.4 Home countries

It is possible that the soccer fans of a hosting country experience the tournament more intense as the whole country is under the spell of this event, and so soccer results might have a stronger effect on local stock markets of hosting countries than on local stock markets of other nations. From a rational point of view there can be a stronger stock reaction because there are considerable economic benefits for a hosting country.

Table 6

Difference Between The Effect of Soccer Results on

Stock Returns for Hosting Countries and Other Nations

I estimate the following model, consisting of two interaction terms, using a GLS estimator and random effects model

$$\hat{\varepsilon}_{it} = \beta_0 + \beta_1 home + \beta_2 W_{it} + \beta_3 L_{it} + \beta_4 {*}home{*}W_{it} + \beta_5 {*}home{*}L_{it} + u_{it}$$

where $\hat{\varepsilon}_{it}$ are the normalized abnormal returns obtained from regression (1). 'Home' is a dummy variable that is one if country i hosts the tournament during a match on day t and zero otherwise. W_{it} is a dummy variable that is one if country i wins a match on day t and zero otherwise. L_{it} is a loss dummy and is defined similarly. My sample consists of 11 home countries, and 16 non-home countries. The sample period is from January 1st, 1973 to December 31st, 2012.

	Days	ß	z-values
Home	43	0,016	1,03
W_{it}	23	0,002	0,06
Home* W_{it}		0,152	0,88
L_{it}	12	-0,002	-0,06
Home* L_{it}		0,175	0,74

In table 6, I test whether the effect of match outcomes on stock returns is stronger for countries that host the tournament during a match than for non-hosting nations. I look at the interaction between the effect of being a home country and the effect after a win and loss. If home countries react stronger after a win and/or loss than non-hosting countries, I should find a positive interaction effect.

The interaction coefficient of the win and home dummy is 0,152, but insignificantly different from zero. This indicates that there is no significant difference between the effects on stock prices when a home country or a non-home country wins a game. Moreover, the reported result of the interaction term between a home country and a loss is also insignificant, 0,175 (z-value=0,74). These results indicate that the effect of soccer results on stock returns is not stronger for home than non-home countries.

It could also be that the difference between the two effects is not significant, but that there is an effect after a win or loss in one of the samples. To test this, I run regression (2) for home and non-home countries separately. However, I do not find an effect for both groups, indicating that soccer results do not affect stock prices in home countries or in non-home countries. For brevity, the results are reported in panel A and B of table A7 in the Appendix.

These results imply that the effect of soccer results on stock prices for countries that hosts the event is not significantly different from the effect for non-hosting countries, nor do I find evidence that there is a relationship between soccer results and stock returns in home or non-home countries separately.

5.5 Before and after the euro

In this section, I test whether the entrance of the euro has changed the effect of soccer results on stock returns. The entrance of the euro has caused the home bias to decrease in Europe, and investors now divide their investments over multiple stock markets instead of investing mainly in domestic stocks.

I test whether there is a difference before and after the euro with an interaction term between a time dummy to describe whether a match is played before or after the euro, and a win and loss dummy. I estimate the model for euro and non-euro countries, where the latter is the control group. If the effects are indeed different, I should find an interaction effect between the dummy 'after euro' and the win and/or loss dummy for euro-countries. Note that I do not expect to find a significant interaction effect for non-euro countries, as nothing has changed for them in terms of currency. If I find a significant interaction effect for both groups, this would indicate that other factors might have played a role too.

Table 7 reports the results, where Panel A includes euro countries. The coefficient of 'after euro' is -0,012 and significant at the 5% level, indicating that playing a match after the entrance of the euro has a negative effect on stock returns. I find negative interaction coefficient estimates between this time dummy and wins and losses, but these values, -0,059 and -0,049, respectively, are insignificantly different from zero. These results imply that the effects of wins and losses on stock returns do not differ before and after the euro for euro countries.

These results indicate that playing a match after 2002 has a negative effect on stock returns. However, the effect after a win or loss on stock returns before the euro is not different from the effect after the euro.

For non-euro countries, there is a positive effect of losses of 0,138, which indicates that there is a positive stock reaction after a loss in a non-euro country. This result is counterintuitive, because a loss is a negative result. However, the coefficient estimate is only significant at the 10% level, or it can be due to chance.

Table 7

Difference Between The Effect of Soccer Results on

Stock Returns Before and After the Euro

I estimate the following model, consisting of two interaction terms, using a GLS estimator and random effects model

$$\hat{\varepsilon}_{it} = \beta_0 + \beta_1 \text{after euro} + \beta_2 W_{it} + \beta_3 L_{it} + \beta_4 {*}\text{after euro}{*}W_{it} + \beta_5 {*}\text{after euro}{*}L_{it} + u_{it}$$

where $\hat{\varepsilon}_{it}$ are the normalized abnormal returns obtained from regression (1). 'After euro' is a dummy that is one if a match is played in 2002 or later and zero otherwise. W_{it} is a dummy variable that is one if country i wins a match on day t and zero otherwise. L_{it} is a loss dummy and is defined similarly. I estimate the model twice, once for euro countries and once for non-euro countries. My sample consists of 14 euro-countries and 13 non-euro countries. The sample period is from January 1st, 1973 to December 31st, 2012.

	Days	ß	z-values
Panel A: Euro countries			
All games	1.101		
After euro		-0,012	-2,44*
W_{it}	567	0,019	0,42
After euro * W_{it}		-0,059	-0,86
L_{it}	316	-0,020	-0,32
After_euro * L_{it}		-0,049	-0,54
Panel B: non-Euro countries			
All games	804		
After euro		0,000	0,01
W_{it}	403	0,026	0,41
After euro * W_{it}		-0,002	-0,03
L_{it}	223	0,138	1,78**
After_euro * L_{it}		-0,134	-1,21

*: Significant at the 5% level

**: Significant at the 10% level

It could also be that the effects before and after 2002 are not different, but that there is an effect of soccer results on stock returns before or after 2002. To test this, I run regression (2) with data before and after 2002 separately, and do this for euro and non-euro countries. For the euro countries, the coefficient estimates before and after 2002 are both insignificant for wins and losses, indicating that there is no effect before or after 2002. Regarding the non-euro countries, I find a positive effect after a loss before 2002, indicating that losses had a positive effect on the stock market before 2002. Similar to the result in table 7, this result is only marginally significant. For brevity, the results are reported in panels C to F of table A7 of the Appendix.

Even though evidence is found that the home bias has decreased after 2002, this does not seem to have an influence on the relationship between soccer results and stock returns. I do not find a difference between the effects before and after 2002 for euro countries. Moreover, my results indicate that there is no effect of soccer results on stock returns in both periods, making it unlikely to observe a difference. Furthermore, I find evidence that playing a match after 2002 has a negative effect on stock prices in euro-countries. For non-euro countries, I report a positive effect after a loss, but this is only significant at the 10% level. Based on the results discussed in this section, I reject Hypothesis 4. My results do not indicate that the effect of soccer results on stock returns is less strong after the euro than before the euro.

5.6 Probabilities and stock reactions

There can be a stock reaction according to a match result, and investors can still be perfectly rational, as they react on the economic consequences of soccer matches. If they expect a loss, they incorporate the negative economic consequences in their stock prices, assuming that there are economic consequences after a match result. According to the EMH, investors update their expectations immediately when they receive new information so if they expected a loss, and a win occurs, they have to update their expectations and this will be reflected on a country's stock market. If this is the case, there should be a relationship between the ex ante probability that a country will win a match, and stock returns. In other words, if the probability is low that a country will win, I should find a stronger stock reaction after a win than if the probability of a win is high, and the same applies for losses.

In this section, I will discuss whether ex ante probabilities of a match outcome have a relationship with stock reactions. In order words, if an unexpected loss or win leads to a stronger stock reaction than an expected match outcome.

Table 8

Probabilities and Abnormal Daily Stock

Returns after International Soccer Results

I estimate the following model, consisting of two interaction term, using a GLS estimator and random effects model

$$\hat{\varepsilon}_{it} = \alpha_0 + \alpha_1 W_{it} + \alpha_2 P_{it} + u_{it}$$

where $\hat{\varepsilon}_{it}$ are the normalized abnormal returns obtained from regression (1). W_{it} consists of dummy variables for wins overall and in close qualification, group and elimination games, called W_{it}, W_{it_qr} W_{it_gs} and W_{it_el}, respectively, and is one if country i wins a game in stage g on day t, and zero if it loses a match. P_{it} is the ex ante probability that country i wins a match on day t. My sample consists of only match days with a win or loss as a result, from September 5th, 1974 to July 2nd, 2012.

	Days	α	z-value
	Panel A: All wins		
All wins	970	0,026	0,54
Probability	925	-0,015	-0,64
Intercept		-0,010	-0,25
	Panel B: Wins in different subcategories		
Elimination games	42	-0,039	-0,33
Group games	111	0,096	1,21
Qualifying games	806	0,024	0,47
Probability	914	-0,014	-0,57
Intercept		-0,012	-0,30

Table 8 reports the results of this analysis, using normalized abnormal returns. This sample consists of only match days with a win and loss as result. As a consequence, the win dummy I estimate in my model is one if a match is won, and zero if it is lost. I estimate the model once with the overall win dummy, to capture the effect of a win in general and once with the win dummies for subgroups. The effect of a loss is picked up by the intercept α_0 and controls for the ex ante probability that country i wins a match (Edmans, García & Norli, 2007). The intercept of both models is negative but insignificant, -0,010 for the overall model, and -0,012 for the subgroups model, not finding any evidence for the loss effect.

The effect after a win can be calculated by summing α_0 and α_1 of equation (9) which are the intercept and the coefficient of the win dummy. The magnitude of the overall win coefficient is five times larger than the overall win coefficient in table 3 (which is 0,005), but still insignificant. The other win coefficients have the same sign as the coefficients in table 3, and are insignificant. The coefficient estimate of the probability variable is -0,015 in the model with overall wins, and -0,014 in the model with game subgroups. These insignificant results imply that ex ante probabilities have no effect on stock returns, and that investors do not react more strongly to an unexpected outcome than an expected one.

According to these results, I do not find a relationship between ex ante probabilities and stock returns, implying that probabilities can not explain whether investors react more strongly to unexpected results than to expected match outcomes. Probabilities can not be used as an explanation for abnormal returns after international soccer results, and I reject Hypothesis 5.

6. Conclusion

The traditional view that investors are rational, and that they make choices that maximize their expected utility is long gone. According to the behavioral finance framework, markets are not expected to be efficient, as there are some major deviations from this efficiency, mainly caused by investor behavior. Research confirms the view that investor sentiment has a considerable impact on the way investors price assets, and therefore stock returns. Over the past years, studies have identified several events that influence investor behavior, for instance holidays, hours of daylight, and soccer results. As these events have an effect on investor sentiment, and mood impacts the way investors behave on the stock market, it is interesting to test whether the impact of these events on investor mood are reflected on the stock market as well.

This paper examined the effect of sudden changes in investor mood, caused by European soccer results, on local markets stock returns. Studying soccer results of 10 European Championships and abnormal stock returns from 1973 to 2012, I do not find evidence that there is a relationship between soccer results and stock returns.

The results of my main regression are insignificant for both wins and losses, 0,039 and 0,024, respectively, indicating that local stock market are not affected by soccer results the first trading day after the match. Contrary to Edmans, García and Norli (2007), I do not find evidence that investors react more strongly to a loss than to a win.

Within soccer matches, I distinguish between three subgroups of games: qualification games, groups games and elimination games. I do not find an effect after a non-elimination game, but there is no effect after an elimination game either. I expected a stronger reaction after games in this stage, as from a rational point of view, there are direct consequences after an elimination game, where the negative consequences after a loss are larger than the positive consequences after a win. According to the theory of loss aversion, losses loom larger than gains, which could increase this effect. Contrary to my expectations, wins and losses in elimination games do not seem to affect stock returns the first trading day after a match.

To test whether my results are robust to methodological changes, I perform several robustness checks. I apply a fixed effects model, panel corrected standard errors, I trim my sample for outliers and include all close qualification games instead of only the close ones. Applying these models changes my results slightly, but the overall thrust remains the same. After trimming my sample for outliers, the coefficient estimates have become closer to zero. Removing the 10% most extreme raw abnormal returns changes the coefficient estimates of wins and losses to respectively -0,003 and -0,007.

As there are various reasons why certain countries or time periods might exhibit a relation between soccer outcomes and stock returns, I estimate my model for several subgroups. I test the effect of match outcomes on stock returns for seven so-called soccer nations and for countries that host a Championship, but I find similar, insignificant results.

The home bias is an important assumption to test the relationship between soccer results and stock returns. If soccer results affect investor mood, and these mood changes have an impact on the stock market, it is essential to assume that investors invest in domestic stocks. If they do not, the effect of a soccer result on investor mood will not be reflected on the local stock market of that country's soccer team, but will be divided over multiple stock markets.

As Giofré (2008) and Schoenmaker and Bosch (2008) find evidence that the home bias in Europe has decreased after the entrance of the euro, I study whether there is a difference in the effect of soccer results on stock returns before and after 2002. I find evidence that playing a match after 2002 has a negative effect on stock returns of -0,012, but the effect before 2002 is not different from the effect after 2002. For non-euro countries, there is a positive effect after losses, implying that a loss has a positive effect on stock returns. This effect is counterintuitive as losing a game is something negative, but the result is only significant at the 10% level, or can also be due to chance.

Edmans, García and Norli (2007) argue that soccer results can have an effect on stock markets while agents can still be rational if they react on the economic consequences after a soccer match. Assuming that soccer results have an impact on economic activity, investors incorporate the consequences of the expected outcome of a match in their asset pricing. However, if there is an unexpected match outcome, they have to update their expectations and it is likely that there will be a stronger stock reaction. In this case, investors would still be rational and there is no violation of EMH. I test whether there is a relationship between match outcome probabilities and stock returns, and similar to research by Edmans, García and Norli (2007), my results indicate that there is no effect of match outcome probabilities on stock returns, implying that investors do not react stronger to unexpected outcomes than expected results. If there would have been a stock reaction after a soccer result, this could not be addressed to investors updating their expectations.

To conclude, the results of this paper do not indicate that that there is a relationship between soccer results and stock returns, nor do I find evidence that there is a stronger reaction following a loss than after a win.

7. Discussion

In this section, I will first discuss the main implications of my paper and I will make some remarks on my statistical model. Finally, I will give recommendations for future research.

There are numerous studies supporting the view that investor mood influences stock returns. Edmans, García and Norli (2007) investigate this relation using soccer results as an event that is likely to affect mood, and contrary to this study, they find a significant effect of soccer results on stock returns, but only after losses. Other studies examining this relationship report contrary results. Gallagher and O'Sullivan (2011) and Klein, Zwergel and Heiden (2009) study soccer results in two European countries, Ireland and England, but do not find evidence that soccer results of these European countries affect local stock market returns.

There are three possible explanations for the fact that I do not find a relationship between soccer results and stock returns. First of all, it is possible that investor mood does not impact stock returns. In other words, soccer results do impact investor mood, but this mood is not reflected on the stock market. Second, it could be that investor mood does impact stock returns, but that soccer results do not have an effect on investor mood. Finally, it can also be that there is a relationship between soccer results and stock market returns, but not in Europe. Edmans, García and Norli (2007) study besides World Cups also continental cups, including European Championships. For these continental cups, they only report a negative effect after lost elimination games and find no effect after a win. It is possible that the effects they report in their paper are driven by results from World Cups or countries outside Europe, and that their results after European soccer matches are insignificant too. Unfortunately, they did not report their results for European Championships separately so I can not verify this.

Even though the home bias has decreased after the entrance of the euro, and investors invest less in their country's local stock market, I do not find a difference between the effect of soccer results on stock returns before and after 2002. This result can either imply that investors did not invest less in their domestic stock market, in other words, the home bias has not decreased, or it can mean that there is no relationship between soccer results and stock returns in both time periods, and so it is unlikely to find a difference. I examined this relationship for both time periods separately, and found no effect before or after 2002, so I find it reasonable to assume that the latter is the case.

Finally, I do not find a stronger stock reaction after unexpected match outcomes than after expected match outcomes, which can imply the following. First, this finding can indicate that soccer results do not have economic consequences. If this is the case, it is perfectly rational that investors do not take match outcome probabilities into account as soccer results are irrelevant to the economic activity of a country. It could also mean that soccer results have economic consequences, but that investors refuse to take them into account. If there would be a stock reaction after a soccer match, this reaction would be caused by something else, for example the change in investor mood due to this match outcome. Even though organizing a Championship has economic benefits for a county, Edmans, García and Norli (2007) argue that soccer matches in general have small economic impact and therefore, I find the first argument more likely.

According to the Efficient Market Hypothesis, stock prices only change when new information becomes available, and changes in mood caused by soccer results should not play a role on the stock market. If there would be a stock market reaction after soccer results, due to a sudden change in investor mood, this would be a violation of the semi-strong and strong form of the Efficient Market Hypothesis. Soccer results are public information, and according to these forms of EMH, this information should already be incorporated in stock prices, and it would not be possible for investors to earn excess returns by trading on these match outcomes. However, as I do not find an effect, I can not reject any form of the Efficient Market Hypothesis or reject the null hypothesis that markets are efficient.

The main implication of this paper is to give insight in the relationship between investor mood and stock returns, where soccer results are used as an event that is likely to influence mood. Understanding how soccer results impact stock returns can be used to develop a trading strategy, but is rather difficult as soccer results are not known in advance. Moreover, the transaction costs involved would probably prevent investors from trading on soccer matches. Rather than suggesting potential trading strategies, the goal of this paper is to give insight in factors that influence investor mood to better understand the relationship between investor behavior and stock reactions.

The fact that my results are barely significant is not that remarkable, as the dependent variable of my model are abnormal returns, which are assumed to be zero. Moreover, my sample consists of 290.223 trading days without a match, and 1.951 trading days associated with a match outcome, which is only a small part of the total trading days. However, Edmans, García and Norli (2007) use a similar ratio of match and non-match days and they do report significant results.

The R^2 of the models I estimate is very low, often zero or 0,001%, implying that my model explains only a minor part of the variation in abnormal returns. However, this is not strange, as these abnormal returns are the residuals of regression (1). This model was already not able to explain these returns, and it would have been surprising if only 1.951 soccer results were able to explain thousands of abnormal returns.

A remark on this study is that there are many more days not associated with a match than match days in my sample, which makes it less likely to find significant results. For future research, it would be interesting to look at the results of an international soccer competition as the Champions League. Hereby, it is possible to collect more results in a shorter time period, as this competition is played every year. Moreover, as only the best soccer teams from Europe can participate in this competition, it is likely that the results will have an impact on people's mood. One thing to take into account is that sometimes several soccer teams of a country participate in the competition. To avoid conflicting effects (a win of one team and a loss of another team on the same day), I recommend to consider days where only one soccer team of a country played a match, or where the match outcomes are similar (all soccer teams won or lost). Still, as inhabitants of a country support many different soccer team instead of one national team, it is questionable whether a match outcome of one team will affect enough investors to find an effect.

Even if investors are aware of the possible effects of soccer results on stock returns, it is unlikely for them to develop a trading strategy based on this knowledge, as individual soccer results are not known in advance. Kaplanski and Levi (2008) examined the aggregate effect of the World Cup on the U.S. stock market and report a negative effect after each tournament. As this negative effect persists over multiple years, they argue that it can be known in advance and that investors can develop a trading strategy to exploit this effect. It would be interesting to investigate the aggregate effect of European Championships to see if there is a similar effect for European soccer matches.

Appendix

Table A1

Overview of Countrycodes and Countries

Code	Country	Code	Country	Code	Country
BE	Belgium	GE	Germany	OE	Austria
BG	Bulgaria	GR	Greece	PL	Poland
CP	Cyprus	HN	Hungary	PT	Portugal
CR	Czech Republic	IR	Ireland	RM	Romania
CT	Croatia	NL	Netherlands	RS	Russia
DK	Denmark	NR	Norway	SE	Sweden
EN	England	IS	Israel	SV	Slovenia
ES	Spain	IT	Italy	SW	Switzerland
FN	Finland	LX	Luxembourg		
FR	France	MT	Malta		

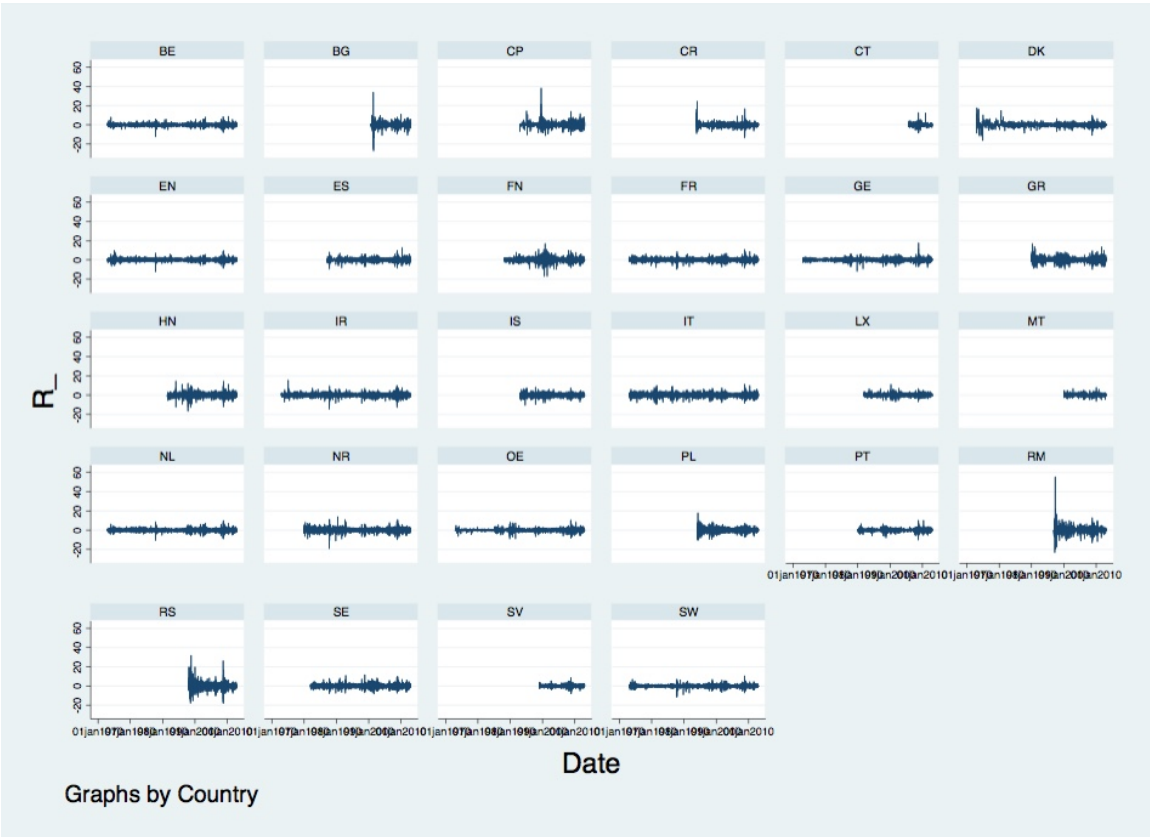

Figure A1. Returns per country

Table A2

Overview of Average Return and

Amount of Wins and Losses per Country

Country	Time Series Begins	Mean Return	Wins	Losses
Belgium	01-01-73	0,041	37	26
Bulgaria	02-10-00	0,08	13	9
Cyprus	23-12-92	0,018	11	25
Czech Republic	09-11-93	0,048	49	14
Croatia	03-10-05	0,027	21	5
Denmark	01-01-73	0,05	50	34
England	01-01-73	0,05	53	17
Spain	02-03-87	0,039	62	14
Finland	25-03-88	0,049	21	24
France	01-01-73	0,049	63	18
Germany	01-01-73	0,035	76	17
Greece	01-01-90	0,043	40	19
Hungary	21-06-91	0,062	19	21
Ireland	01-01-73	0,049	40	25
Israel	01-01-93	0,041	21	17
Italy	01-01-73	0,046	57	18
Luxembourg	02-01-92	0,048	5	41
Malta	04-01-00	0,014	1	25
Netherlands	01-01-73	0,043	76	24
Norway	02-01-80	0,055	36	23
Austria	01-01-73	0,033	28	33
Poland	01-03-94	0,032	19	14
Portugal	02-01-90	0,022	46	15
Romania	06-12-96	0,102	24	8
Russia	27-01-98	0,132	30	12
Sweden	04-01-82	0,062	42	20
Slovenia	31-12-98	0,017	15	17
Switzerland	01-01-73	0,033	26	29

Table A3

Abnormal Daily Returns after International Soccer Results Using a Fixed Effects Model

I estimate the following model, using a GLS estimator and fixed effects model

$$\hat{\varepsilon}_{it} = \beta_0 + \beta_W W_{it} + \beta_L L_{it} + u_{it},$$

where $\hat{\varepsilon}_{it}$ are the normalized abnormal returns obtained from regression (1). W_{it} consists of dummy variables for wins overall and in close qualification, group and elimination games, called W_{it} W_{it_qr} W_{it_gs} and W_{it_el}, respectively, and is one if country i wins a game in stage g on day t, and zero otherwise. L_{it} are similar dummy variables for losses, called L_{it}, L_{it_qr} L_{it_gs} and L_{it_el}. I will estimate this model once with the overall win and loss dummy to capture the effect of a win and loss in general, and once including subgroups. My sample consists of 28 countries when using raw returns and 27 countries when using normalized returns and covers the period from January 1st, 1973 to December 31st, 2012.

	Wins			Losses		
	Days	$ß_W$	z-values	Days	$ß_L$	z-values
Panel A: Abnormal Raw Returns						
All games	981	0,039	1,05	564	0,024	0,49
Elimination games	42	-0,033	-0,18	38	-0,140	-0,75
Group games	111	0,140	1,28	91	0,086	0,71
Close qual. games	149	0,103	1,09	126	0,030	0,29
Panel B: Abnormal Normalized Returns						
All games	970	0,005	0,20	539	0,002	0,06
Elimination games	42	-0,040	-0,32	38	-0,022	-0,17
Group games	111	0,084	1,09	91	0,021	0,25
Close qual. games	146	0,046	0,69	125	0,019	0,26

Table A4

Abnormal Daily Returns after International Soccer Results Using Panel Corrected Standard Errors

I estimate the following model, using a GLS estimator and panel corrected standard errors

$$\hat{\varepsilon}_{it} = \beta_0 + \beta_W W_{it} + \beta_L L_{it} + u_{it},$$

where $\hat{\varepsilon}_{it}$ are the normalized abnormal returns obtained from regression (1). W_{it} consists of dummy variables for wins overall and in close qualification, group and elimination games, called W_{it} W_{it_qr} W_{it_gs} and W_{it_el}, respectively, and is one if country i wins a game in stage g on day t, and zero otherwise. L_{it} are similar dummy variables for losses, called L_{it}, L_{it_qr} L_{it_gs} and L_{it_el}. I will estimate this model once with the overall win and loss dummy to capture the effect of a win and loss in general, and once including subgroups. My sample consists of 28 countries when using raw returns and 27 countries when using normalized returns and covers the period from January 1st, 1973 to December 31st, 2012.

	Wins			Losses		
	Days	$ß_W$	z-values	Days	$ß_L$	z-values
Panel A: Abnormal Raw Returns						
All games	981	0,039	0,79	564	0,024	0,43
Elimination games	42	-0,033	-0,19	38	-0,140	-0,77
Group games	111	0,140	1,26	91	0,086	0,65
Close qual. games	149	0,103	0,94	126	0,030	0,26
Panel B: Abnormal Normalized Returns						
All games	970	0,005	0,15	539	0,002	0,05
Elimination games	42	-0,040	-0,29	38	-0,022	-0,16
Group games	111	0,084	0,95	91	0,021	0,23
Close qual. games	146	0,046	0,66	125	0,019	0,24

Table A5

Abnormal Daily Returns after International Soccer Results Using Trimmed Outliers

I estimate the following model, using a GLS estimator and random effects model

$$\hat{\varepsilon}_{it} = \beta_0 + \beta_W W_{it} + \beta_L L_{it} + u_{it},$$

where $\hat{\varepsilon}_{it}$ are the abnormal returns obtained from regression (1). W_{it} consists of dummy variables for wins overall and in close qualification, group and elimination games, called W_{it} W_{it_qr} W_{it_gs} and W_{it_el}, respectively, and is one if country i wins a game in stage g on day t, and zero otherwise. L_{it} are similar dummy variables for losses, called L_{it}, L_{it_qr} L_{it_gs} and L_{it_el}. To exclude the most extreme returns, I removed the highest and lowest 5% of the raw and normalized abnormal returns. I will estimate this model once with the overall win and loss dummy to capture the effect of a win and loss in general, and once including subgroups. My sample consists of 28 countries using raw abnormal returns and 27 countries when I use normalized abnormal returns. The sample period is from January 1st, 1973 to December 31st, 2012.

	Wins			Losses		
	Days	$ß_W$	z-values	Days	$ß_L$	z-values
Panel A: Abnormal Raw Returns						
All games	981	-0,003	-0,12	564	-0,007	-0,23
Elimination games	42	0,014	0,12	38	0,001	0,00
Group games	111	0,055	0,86	91	-0,067	-0,93
Close qual. games	149	0,043	0,76	126	-0,029	-0,47
Panel B: Abnormal Normalized Returns						
All games	970	0,005	0,26	539	-0,025	-1,03
Elimination games	42	0,073	0,80	38	0,011	0,12
Group games	111	0,037	0,72	91	-0,042	-0,71
Close qual. games	146	0,017	0,37	125	-0,013	-0,26

Table A6

Abnormal Daily Returns after International Soccer Results Including All Qualification Games

I estimate the following model, using a GLS estimator and random effects model

$$\hat{\varepsilon}_{it} = \beta_0 + \beta_W W_{it} + \beta_L L_{it} + u_{it},$$

where $\hat{\varepsilon}_{it}$ are the normalized abnormal returns obtained from regression (1). W_{it} consists of dummy variables for wins overall and in close qualification, group and elimination games, called W_{it} W_{it_qr} W_{it_gs} and W_{it_el}, respectively, and is one if country i wins a game in stage g on day t, and zero otherwise. L_{it} are similar dummy variables for losses, called L_{it}, L_{it_qr} L_{it_gs} and L_{it_el}. I will estimate this model once with the overall win and loss dummy to capture the effect of a win and loss in general, and once including subgroups. My sample consists of 27 countries and covers the period from January 1st, 1973 to December 31st, 2012.

	Wins			Losses		
	Days	$ß_W$	z-values	Days	$ß_L$	z-values
All games	970	0,005	0,20	539	0,002	0,06
Elimination games	42	-0,040	-0,32	38	-0,023	-0,17
Group games	111	0,084	1,09	91	0,021	0,25
Qualification games	806	-0,001	0,03	404	0,002	0,05

Table A7

Abnormal Daily Returns after International Soccer

Results for Home and Euro countries

I estimate the following model, using a GLS estimator and a random effects model

$$\hat{\varepsilon}_{it} = \beta_0 + \beta_W W_{it} + \beta_L L_{it} + u_{it},$$

where $\hat{\varepsilon}_{it}$ are the normalized abnormal returns obtained from regression (1). W_{it} is a dummy variables for wins overall and is one if country i wins a game on day t, and zero otherwise. L_{it} is a similar dummy variable for losses. My sample consists of 11 Home countries and 15 Euro countries when using normalized returns and covers the period from January 1st, 1973 to December 31st, 2012.

	Wins			Losses		
	Days	$ß_W$	z-values	Days	$ß_L$	z-values
	Panel A: Home countries					
All games	23	0,154	0,79	12	0,173	0,64
	Panel B: Non-home countries					
All games	947	0,002	0,06	527	-0,002	-0,06
	Panel C: Euro countries after 2002					
All games	255	-0,039	-0,82	161	-0,070	-1,15
	Panel D; Euro countries before 2002					
All games	312	0,019	0,41	155	-0,020	-0,31
	Panel E: non-Euro countries after 2002					
All games	228	0,023	0,49	110	0,0044	0,06
	Panel F: non-Euro countries before 2002					
All games	175	0,026	0,38	113	0,138	1,65*

*: Significant at the 10% level

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