BI Norwegian Business School - campus Oslo

GRA 19502

Master Thesis

Component of continuous assessment: Thesis Master of Science

Investor Sentiments and Stock Returns

Navn: Mikal Dahl Jørgensen, Syver Gåsbakk

Start: 02.03.2017 09.00

Finish: 01.09.2017 12.00

Name of students:

Syver Gåsbakk

Mikal Dahl Jørgensen

Study program:

Master of Science in Business, Major in Finance

Date of submission:

01.09.2017

This thesis is a part of the MSc program at BI Norwegian Business School. The school takes no responsibility for methods used, results found and conclusions drawn.

Table of Contents

Abstract

This thesis investigates the stock market reaction to the results of football matches in Argentina, Brazil, England, France, Germany and Spain. The goal of this thesis is to further add on to existing theory of mood variables and the stock market. Two approaches within event study methodology have been used to capture potential effects and a significant decline in the stock market after losses before the financial crisis were found. Some of the findings are also robust to methodological changes, where we first adjust the returns for volatility and secondly, for asymmetric shocks in volatility. Therefore, it is concluded that stock markets were affected by football sentiments before the financial crisis. The stock market is not affected by football sentiments after the financial crisis.

I. Introduction

The assumption of rationality is a major building block in economics. Investors are depicted as flawless and they seek to maximize their utility. However, this strict assumption has proven to be challenging as investors are independent and exude irrational behavior. For this reason, it is not plausible to make an assumption and generalize it over the entire population (Shiller, 2003). Kahneman and Tversky (1986) argue that the actual behavior of investors deviates significantly from what is used in standard theory. There are numerous reasons for this deviating behavior and among them is the current mood of investors. Research has found that certain mood variables have a statistically significant impact on stock markets.

One important research is Edmans, Garcia and Norli (2007), *Sport sentiments and stock returns.* Their paper investigates the stock market reaction to sudden changes in investor mood. They use football results as a proxy for mood, where they claim that there is a statistically significant decline in national indexes when the national team of that country loses a football match. Similar research before 2007 has also found other variables affecting investors' mood.

This thesis is a replication of the investigation by Edmans et al. (2007) in order to tell if their result is still relevant. They use an approach within event study methodology which treats the football results as a continuous variable that affect stock returns. This approach is based on estimating the regression coefficients using all historical data. On the other hand, they refer to a possible single event approach to estimate abnormal returns. The single event approach is different from the continuous variable approach as it measures the coefficients based on an estimation period, rather than all historical data.

To distinguish ourselves from recent and previous research we use the two highlighted approaches, which are both based on event study methodology. Through this approach, we can verify the result of Edmans et al. (2007) while simultaneously controlling for potential research biases. Additionally, a contribution is made with an extended data period, where we emphasize on the difference in investor behavior before and after the financial crisis.

The seven countries Argentina, Brazil, England, France, Germany, Italy and Spain has been examined, and all their qualifying, group and elimination games in world- and continental cups. Edmans et al. (2007) use data until 2004, where we use stock returns and football results from the World Cup in 1963 up until the European Championship in 2016. These seven countries are chosen as football is considered to be of high importance in these countries, and because they have frequently dominated the sport back to the 1960's.

Hence, the following research question has been formulated:

- *Are markets efficient with regards to football sentiments, before and after the financial crisis?*

To check whether the stock markets are efficient, the following hypothesis where the assumption of rational actors is embedded in the null:

H_0: Stock markets are not affected by the outcome of football matches.

H_1: Stock markets are affected by the outcome of football matches.

The remainder of this thesis is structured as follows. Section II gives an overview of previous literature on the topic of mood proxies, as well as different methodologies used. In Section III we present the theoretical framework relevant for the thesis and Section IV explains the methodology. Section V describes the data while Section VI constitutes of the main analysis. Section VII summarizes our findings and conclusion.

II. Literature Review

In this section, a literature review on the topic of mood and its influences on judgement are presented. This section is divided in three parts where we review the topics of mood and risk taking, mood and sports and how studies have used different methodologies to arrive at their final conclusions.

A. Mood, Judgement and Risk Taking

Throughout the last decades, researchers have been interested in how moods impact investors' decision making. Previous research implies that investor decisions are influenced by their current state of mood (Schwarz, 1989). According to Wright and Bower (1992) people who are in a good mood, are more optimistic in their choices and judgement than those in bad mood. In fact, studies have found that bad mood have a tendency to encourage people to engage in detailed analytical activity, while good mood is associated with less critical evaluation of information (Sinclair & Mark, 1995). In a study by Hoffmann, Post and Pennings (2013) this is evident as investors continue trading during the financial crisis in 2008 as they consider the weakened asset prices as a window of opportunity to enter the market.

Hirshleifer (2001) believes that mood and emotions affect people's risk taking and Loewenstein, Weber, Hsee and Welch (2001) argue that the influence of mood in a decision making process is highly prominent in cases where the decision carries risk and uncertainty. In the article "*The Role of Feelings in Investor Decision Making*" by Lucey and Dowling (2005), it is concluded that investors allow their mood state at the time of making an investment to influence their judgement.

Highly cited Schwarz and Clore (1983) found that sunny weather lead people to report a higher level of life satisfaction compared to rainy days. In their article "*Mood as Information: 20 Years Later*" (2003) they state that people ask themselves "How do I feel about this" in evaluative judgments. In doing so, they misread their current feelings as a response to the object of judgment, which in turn results in more favorable evaluations under positive rather than negative moods (i.e. sunny vs. rainy days). Allowing such irrelevant mood states to affect decisions is often labeled mood misattribution and according to Lucey and

Dowling (2008) the relationship between such variables and equity prices are highly popular in the investigation of behavioral finance.

B. Mood, Sports Proxies and Stock Returns

In addition to Edmans et al. (2007), numerous studies investigate the possibility of sports results affecting mood. In a similar fashion, Ashton, Gerrard and Hudson (2003) reported a strong association between the performance of the national team of England and the daily change in the FTSE 100 index. They used daily data from 1984 until 2002 and found a statistically significant decline in the index when the England lost. In addition to the loss effect, they also documented an increase after England won a football match. However, their paper was contradicted by Klein, Zwergel and Fock (2009) who claimed that there were some highly questionable features in the methodology of Ashton et al. (2003). Klein et al. (2009) did not find any statistically significant results between football matches and the stock market.

Boyle and Walter (2003) investigated the impact of mood on the stock market in New Zealand by using the results from the national rugby team as a proxy for mood. Their data was collected from 1950 to 1999. The authors believed that since rugby carries a high standing amongst New Zealanders, results from these matches could affect stock returns. However, they disproved their own beliefs and concluded with no relationship between rugby results and stock returns.

How risk taking behavior is developed was researched by Arkes, Herren and Isen (1988) in the paper "*The Role of Potential Loss in the Influence of Affect on Risk-Taking Behavior*". In their first experiment they analyzed the Ohio State Lottery ticket sales in Central Ohio. On the days following a win by the Ohio State University football team, sales tended to be greater than the days that followed a defeat. They were convinced that this pattern was based on the population being in a better mood after a victory.

One of the most recent papers on the topic of football and sentiments is the article "*Sport Sentiments and Stock Returns: Example of FIFA World* Cups" by Lee and Chiu (2016). They choose to collect data from all participants in World Cups since 2002 and they do not find any evidence of football results affecting returns.

They were inspired by Edmans et al. (2007), but added some additional constraints on their regression and they used opening prices in addition to closing prices to estimate excess stock return.

C. Mood and Methodologies

In research, a line has been drawn between different methodologies. On one hand, the mood proxy is treated as a single event, while on the other hand it is treated as a continuous variable.

Kamstra, Kramer and Levi (2000) employ the former in their investigation of sleeping disorders caused by daylight saving time. They found that the daylight saving time impacts on the financial markets using a simple market model and their result were still valid after controlling for autocorrelation and heteroscedasticity. Another research conducted by Frieder and Subrahmanyam (2004) investigated the effect of nonsecular holidays. They concluded that investors look forward to holidays as they would take greater positions in risky assets in the days prior to holiday. Their methodology was based on the simple market model, where they computed a two day window return on both sides of the event, and used data up until each holiday as estimation window.

On the other side of the literature is the continuous variable approach. Hirshleifer and Shumway (2003) investigate the impact of sunshine on financial markets, Cao and Wei (2005) study the effect of temperature and Yuan, Zheng and Zhu (2006) inspects the relation between lunar phases and stock returns. Common for these studies is the approach of treating the mood proxy as a continuous variable, estimating each abnormal return based on all historical data.

D. Summary

Based on the literature review we can conclude that certain mood variables affect investor judgment. Several of these papers are published before the financial crisis, and this investigation will contribute with new data as well as confirming previous research. The recent paper of Lee and Chiu (2016) concluded that there is no relationship between World Cup football matches and stock returns. We will be able to verify their findings with an even greater data sample and two approaches.

III. Theory

In this section, the underlying theories that concern our hypothesis are introduced. We seek to determine whether or not markets are efficient with regards to football sentiments. Efficient markets have been a frequent topic for investigation since it was concluded by scholars that Maurice Kendall's (1953) findings of random price movements indicated an efficient market and not an irrational one.

A. Efficient Market Hypothesis

The efficient markets hypothesis is a fundament in modern investment theory and practice. According to Fama (1970), a market is said to be efficient when prices always fully reflect all available information. Underlying this hypothesis is the assumption that market participants are rational players who always trade in their own self-interest and make decisions based on complex stochastic optimization problems (Lo, 2005). Fama (1970) concluded in his article *Efficient Capital Markets: A Review of Empirical Work* that market efficiency indeed was present, and the efficient markets hypothesis has in fact showed strong resilience towards empirical evidence (Lo, 2005). However, after several decades of research on the efficient markets hypothesis there has not been developed an agreement about whether markets, especially financial markets, are efficient.

B. Behavioral Finance

In later years and more recent time the assumptions of rationality and their implications for efficient markets have been challenged. The focus in academic discussion has shifted away from economic analyses of time series, towards establishing models of human psychology (Shiller, 2003). Phycologists and experimental researchers have found evidence of violation of the efficient markets hypothesis in the form of behavioral biases (Lo, 2005).

According to Shiller (2003) the usage of the assumption of rationality cannot be anything other than absurd. He claims that for these models to work, it must be the case that rational actors must offset the foolishness or biases of the irrational ones. The efficient markets theory says that when an irrational investor buys stock, smart money sells, and vice versa. This will counter the effect irrational investors create in market prices. However, research has found that smart money not necessarily is in the position of power to drive back markets prices. For example, De Long, Shleifer, Summers and Waldman (1990) found that smart money never would choose to offset the irrational investors since they are too concerned with the risk created by these investors.

However, in relation to market bubbles where prices deviate upwards from fundamental value, there is found evidence of speculative investor behavior through numerous experiments in laboratories (Dufwenberg & Moore, 2005). Evidence show that participants try to buy high and sell at even higher prices, and thus exploiting the irrational actors. This continues until the market collapses, as with any bubble in the financial markets. Noussair, Plott and Riezman (2007) find that the strongest tool to counter the effect of this speculative behavior is learning. This means that by experiencing a collapse once, participants become more reluctant to exaggerated prices and the collapse does not occur again.

Drawing back upon the behavioral biases, the prospect theory of Kahneman and Tversky (1979) illustrates this. Their theory suggests that individuals are far more upset by losses than they are satisfied by equivalent gains. Actually, individuals are so upset by any losses that they are willing to take greater amount of risks with the aim of avoiding any loss at all. If these bad decisions leading to losses have its roots in mood change among investors, there will be a possible domino effect creating trading opportunities.

C. Market Anomalies

Throughout the years there has been a goal amongst researchers to uncover anomalies in the efficient market hypothesis. Anomalies are empirical results that seem to be inconsistent with maintained theories of asset-pricing behavior (Schwert, 2003). If present, anomalies indicate either market inefficiency or inadequacies in the underlying asset-pricing model. Wachtel (1942) found bullish tendencies from December to January in eleven of the fifteen years he analyzed and the remaining four had insignificant bearish movement. This seasonal movement in stock prices is named the January effect and is a part of calendar anomalies. Wachtel evidence of the January effect is also found in later research. Rozeff and Kinney (1976) document a weighty 3.48% averaged market return for January and 0.42% for the remaining months. Another calendar anomaly is the Monday effect. Gibbons and Hess (1981) finds evidence of both positive and negative larger returns on Monday’s, which is consistent with earlier research and the findings of Fama (1965) that the variance on Monday’s are 20% greater than other daily returns.

IV. Methodology

In this section, we explain how the empirical tests are performed and elaborate on the statistical models applied. Two approaches are used, both based on event study methodology. Additionally, there are two types of data, results from football matches and stock returns. The football results are qualitative data which means that dummy variables are used in order to run the desired regressions. Data from the different indexes are quantitative, but these data are often prone to time-varying volatility. Incorporating the dummy variables and correcting for the non-constant volatility represents the main tasks in this thesis.

A. Event Study

The main type of methodology applied in this thesis is event study. Event studies represent an effort to gauge the effect of an identifiable event on a financial variable (Brooks, 2014), thus they are often used to test for market efficiency. In order to separate the impact of football results from other unrelated movement in prices we construct abnormal returns using expected returns.

There are numerous ways to calculate the expected returns and Brown and Warner (1980) found that the simple market model performs well under a wide variety of conditions. The market model is considered to have a potential advantage as it removes the part of the variation that is related to the market portfolio, which in turn lowers the variance of the abnormal returns (Brooks, 2014). MacKinlay (1997) argue that the single factor model is superior since a multifactor model has limited gains, as the marginal explanatory power of additional factors is small. In addition, it will have little reduction in the variance of the abnormal returns. We use the same regression as Edmans et al. (2007), which is an extended version of the market model. We use total return indexes, where dividends are reinvested, and we compute the index returns as $R_{it} = \ln(P_{it}/P_{it-1})$.

We measure the abnormal returns in an [0,1] event window to capture the effect of football results. As we emphasize the difference in investor behavior before and after the financial crisis, the relevant timeframe must be defined. According to Gorton (2010) the financial crisis lasted from December 2007 until June 2009, where both the subprime mortgage crisis and financial crisis are included. Thus, the sample is split from 1963 until 2007 as before the financial crisis and 2009 until 2016 as after the financial crisis. Additionally, we use the whole time series from each start date until each end date, including the financial crisis.

Many of the matches in the dataset are played during the weekend. Just like Edmans et al. (2007), we measure the abnormal return on the first trading day after the game. This implies that matches played on Friday, Saturday and Sunday are measured on Monday. Holidays are treated equally. One possible concern with this approach is that it may lead to a spurious day of the week relationship between football results and stock returns and we explain how we resolve this issue in the following sub section.

B. Continuous Variable Approach

The continuous variable approach is based on the model of Edmans et al. (2007). We estimate abnormal returns while controlling for the Monday effect and other confounding effects by running the regression:

$$R_{it} = \gamma_{0i} + \gamma_{1i}R_{it-1} + \gamma_{2i}R_{mt-1} + \gamma_{3i}R_{mt} + \gamma_{4i}R_{mt+1} + \gamma_{5i}D_t + \gamma_{6i}Q_t + \varepsilon_{it} \quad \textbf{(1)}$$

R_{it} is the daily return on a countries index in local currency. We use local currency to remove the effect of fluctuations in exchange rates. R_{mt} is the continuously compounded daily U.S. dollar return on Datastream's world market portfolio (WMP) on day t. As some local markets may be lagging the world index while other may be leading the index, the model also includes R_{mt-1} and R_{mt+1}. We include these variables to control for the fact that international stock markets are integrated, and therefore correlates across countries. We have to control for this correlation to estimate the clean win and loss effect. R_{it-1} is included to account for any first order serial correlation. $D_t = (D_{1t}, D_{2t}, D_{3t}, D_{4t})$ are dummy variables for Monday through Thursday, and $Q_t = (Q_{1t}, Q_{2t}, Q_{3t}, Q_{4t}, Q_{5t})$ are dummy variables for days which the previously 1 through 5 days are non-weekend holydays.

The most interesting variable in the above regression is the residuals, ε_{it}, which represents the abnormal returns. We estimate the effect of football results using the following equation (Edmans et al., 2007):

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

Where W_{it} is a dummy variable for wins and L_{it} is a dummy variable for losses. Following Edmans et al. (2007), we estimate the regressions as a fixed effects model with panel corrected standard errors (PCSE) which assumes that the error terms u_{it} are mean zero and uncorrelated over time, but allows for heteroscedasticity and contemporaneous correlation across countries. PCSE is an applicable technique as we have a large sample of daily observations and a small number of events (Beck and Katz, 1995).

C. Single Event Approach

The single event approach is slightly different from the continuous variable method. Similar to the continuous variable approach we use equation 1 to estimate abnormal returns, but we estimate the coefficients using an estimation period. Normally, the events and estimation windows should not overlap as the estimation of the expected return should not be affected by unusual price effects that the event period is supposed to capture. For this reason, the estimation window should only contain days of which events do not occur in order for the expected return estimation to be uncontaminated by the event under consideration (MacKinlay, 1997). According to Edmans et al. (2007) the single event approach will achieve a larger signal-to-noise ratio in returns and a more realistic estimate of abnormal returns at any time *t*. However, one disadvantage is that the number of observed events tends to be low, which in turn reduces statistical power.

Armitage (1995) suggest that an estimation period can comprise anything from 100 to 300 days for daily observations. We have chosen to use 90 days as estimation period for three reasons. First, the football matches are often carried out with an interval close to 90 trading days which means we avoid the problem of overlap between event and estimation window, secondly, using 90 days allows us to maintain the number of observations at a reputable level, and third, the effect of the clustering of events occurring in championships will be minor in a 90 days perspective. After running equation 1, we computed the average abnormal return with the following test statistic (Barber and Lyon, 1997):

$$\overline{AR}_t = \left(\frac{1}{N}\right)\sum_{i=1}^{n} AR_{it} \qquad \text{and} \qquad t(\overline{AR}) = \frac{\overline{AR_t}}{\sigma(AR_t)\sqrt{N}}$$

D. Normalizing Returns

One of the flaws of using the PCSE technique is the assumption of constant volatility. French, Schwert and Stambaugh (1987) find that stock index returns have time-varying volatility. Consequently, if one of our football results occurred in a time of which the indexes experienced a highly volatile period it would appear as if these football results themselves created the abnormal return, leaving the standard errors to be biased downward. One example is the England exit from the EU, Brexit, which took place at the same time as England lost in the European Championship. In this period, the stock market was highly volatile (Adesina, 2017).

To cope with this problem, we model stock return volatility using a generalized autoregressive conditional heteroskedasticity (GARCH) model, first developed by Engle (1982) and later generalized by Bollerslev (1986). Edmans et al. (2007) uses the residuals from equation 1 to model the volatility, but in order for us to be consistent in both approaches we first estimate an autoregressive moving average (ARMA) model for all indexes and check for autoregressive conditional heteroscedasticity (ARCH) effects using an Engle test on the squared residuals. If ARCH effects are present, this class of model is deemed appropriate and we estimate a GARCH(1,1) model using the maximum likelihood technique on all indexes. Following Bollerslev (1986) the conditional variance of the index returns, u_{it}, is denoted σ_{it}^2 which is written as:

$$\sigma_{it}^2 = var(u_{it}|u_{it-1}, u_{it-2}, \dots) = E\left[\left(u_{it} - E(u_{it})\right)^2 \middle| u_{it-1}, u_{it-2}, \dots\right]$$

Assuming $E(u_{it}) = 0$, we have that:

$$\sigma_{it}^2 = var(u_{it}|u_{it-1}, u_{it-2}, \dots) = E[u_{it}^2|u_{it-1}, u_{it-2}, \dots]$$

From the GARCH(1,1) specification, the conditional variance equations are given as:

$$\sigma_{it}^2 = \alpha_{0i} + \alpha_{1i}u_{it-1}^2 + \alpha_{2i}\sigma_{it-1}^2 \quad \textbf{(3)}$$

σ_{it}^2 is the index return volatility for index *i* on day *t*, $\alpha_{1i}u_{it-1}^2$ and $\alpha_{2i}\sigma_{it-1}^2$ are the ARCH and GARCH terms respectively. They give information about volatility during the previous period and the fitted variance for the model during the previous period. Further we use the time series $\hat{\sigma}_{it}^2$ to create a new time series of normalized stock index returns in the same manner as Edmans et al. (2007):

$$R_{it}^0 = a_i + b_i \left(\frac{1}{\hat{\sigma}_{it}^2}\right) R_{it} \quad \textbf{(4)}$$

Where a_i and $b_i$are chosen so that the mean of R_{it}^0 equals zero and the standard deviation equals one. This approach will normalize all index returns, which means we have our desired homoscedasticity. The normalized returns, R_{it}^0, are then used in equation 1 and we repeat the procedure for both approaches. We differentiate the results by referring to them as abnormal returns and adjusted abnormal returns.

E. Statistical Robustness Checks

To be confident in our results, robustness checks are conducted. Edmans et al. (2007) used two robustness checks. The first was based on examining the sensitivity of their results to outliers and the second was based on creating portfolios of winners and losers. Their results passed these robustness checks and they concluded with highly significant results. We conduct our own robustness checks by formulating Glosten, Jagannathan and Runkle (GJR) models to account for asymmetry in volatility (Glosten, Jagannathan & Runkle, 1993).

Since the development of the GARCH model, several extensions have been derived to cope with the weaknesses tied to the model. One of the main restrictions is related to asymmetry, where positive shocks have less effect on the conditional variance in contrast to negative shocks (Engle & Ng, 1993). This is also known as the leverage effect. Edmans et al. (2007) found a significant negative abnormal return after football matches, but they did not control for asymmetries. This means that their results might be influenced from negative shocks being more persistent on the conditional variance.

We test for this asymmetry using the Sign and Size Bias test, or Engle and Ng test (Engle & Ng, 1993), which is based on the following regression:

$\hat{u}_{i,t}^2 = \phi_0 + \phi_1 S_{it-1}^- + \phi_2 S_{it-1}^- u_{it-1} + \phi_3 S_{it-1}^+ u_{it-1} + v_{it}$ **(5)** where:
$H_0 = \phi_1 = \phi_2 = \phi_3 = 0$

From Engle and Ng (1993) we have that $\hat{u}_t^2$ is the residuals from the GARCH(1,1) model for each index. $S_{it-1}^{-}$is an indicator dummy that takes the value 1 if $\hat{u}_{it-1} < 0$ and zero otherwise. If positive and negative shocks to $\hat{u}_{it-1}$ impact differently upon the conditional variance, then ϕ_1 will be statistically significant. $S_{it-1}^{-}u_{it-1}$ where S_{it-1}^{-} in this case works as a slope dummy variable to control for the magnitude of negative shocks. Lastly, $S_{it-1}^{+} = 1 - S_{it-1}^{-}$, to control for positive shocks. It is possible to split equation 5 in three regressions, and test each independent variable separately. However, Engle and Ng (1993) propose a joint test by running equation 5.

To find an outcome to the null hypothesis we use the Lagrange Multiplier (LM) test (Engle & Ng, 1993), under the hypothesis that:

$$T * R^2 \sim \chi^2 \quad \text{where:}$$

T is the number of observations in the sample and R^2 is the R-squared obtained from equation 5, which will asymptotically follow a χ^2 distribution with three degrees of freedom under the null hypothesis that there is no asymmetries in volatility.

If there exist asymmetry in volatility, we add an additional term to our GARCH(1,1) models, by using the GJR model (Engle & Ng, 1993). The conditional variance equation is now:

$$\sigma_t^2 = \alpha_0 + \alpha_{1i}u_{it-1}^2 + \alpha_{2i}\sigma_{it-1}^2 + \gamma_i u_{it-1}^2 I_{it-1} \qquad \textbf{(6)} \qquad \text{where:}$$

$$I_{it-1} = 1 \; if \; u_{it-1} < 0$$

$$I_{it-1} = 0 \; otherwise$$

After modeling the GJR model, we repeat the procedure of normalizing returns using equation 4. We get a new asymmetry adjusted abnormal return time series, R_{it}^1, and use this new time series in both approaches in the same manner as before.

V. Data

In this section, the data used in this thesis is presented. We intend to explain the sources we have used, how the data has been collected and present descriptive statistics. The thesis constitutes of two types of data sources, football results and index returns. The countries we examine in this thesis are Argentina, Brazil, England, France, Germany, Italy and Spain.

A. Football

Edmans et al. (2007) argue that a proxy for mood needs to fulfill certain characteristics in order to affect returns. First, the variable needs to drive mood in a substantial matter and be strong enough to appear in asset prices. Secondly, it has to affect a large proportion of the population, so it is reasonable to assume that it affects investors. Lastly, the effect must be correlated across the majority of individuals within a country. In total, they claim that football results satisfy these characteristics and use this assumption for all their 39 investigated countries.

Together, the professional football leagues in England, France, Germany, Italy and Spain represent 80% of the football revenues in Europe and they are known through the industry as the “Big Five” (Edmans et al., 2007). With Argentina and Brazil, these seven nations continuously occupy the top world rankings. In several of these countries, the public broadcasters are obligated to show football games live and cable channels are not allowed to bid for the rights to games. In addition, in Italy and Spain the bestselling newspapers are devoted to sports (Edmans et al., 2007). Any mood proxy must be of such magnitude that it affects enough investors. Using these seven countries to determine any effect seems reasonable given the characteristics of a mood proxy.

Edmans et al. (2007) highlight the index movements in these seven countries, but they also employ the same reasoning on their remaining 32 countries without further argumentation. We believe that this decision can create a biased model as abnormal returns are being generated from countries where the general expectation for a win or loss in football matches is low and where the characteristics are not likely to hold. For instance, they include Norway in their sample, and it seems unreasonable to claim that the same characteristics that yield for the seven countries are also fulfilled in the winter nation Norway.

Another possible concern with their sample is abnormal returns with origin from emerging markets. The Datastream's WMP is mostly constructed of returns from developed nations and shocks to emerging markets will not be captured, which in turn will wrongly affect the abnormal return estimate (Edmans et al., 2007).

We collect football results from January 1973 to July 2016 from the official webpage of Fédération Internationale de Football Association (FIFA). The data consist of games from the FIFA World cup, as well as all the continental cups, the European Championship and the Copa America. Through the years the competitions have been constructed in different ways, especially on how to proceed in the competition. One possible way to conduct this event study is to differentiate between types of games, i.e. qualifying games, group games and elimination games. Doing so requires enough data, and in some instances we end up with too little data to draw any statistically significant conclusion.

B. Stock Index Returns

The market indexes we use in this thesis are from Datastream. We calculate returns using a total return index, where dividends are reinvested. These total return indexes are also used by Edmans et al. (2007) and are found in Datastream with the mnemonic that starts with "TOTMK". Additionally, we retrieve the Datastream's world market portfolio, which we use as market return. We measure all index returns in local currencies as the potential biases we examine are related to domestic investors.

Table I presents descriptive statistics of the total return indexes in each country. By looking at the median, we experience more positive log returns than negative ones for all countries. Combined with the mean we can say that the negative values are more substantial than the positive values in England, Germany and Spain. The opposite is true for Argentina, Brazil, France and Italy. The lowest kurtosis score is 5.402 in France, indicating the presence of a leptokurtic distribution in all countries. This is consistent with the Jarque-Bera statistic, which rejects the null hypothesis of normality. For Argentina, England and Italy we also suspect a possible leverage effect due to the fact that the minimum value is greater in absolute value, in comparison with the maximum. However, these values are most likely a result of outliers and should therefore be treated as such.

A graphical inspection of the log returns reveals that volatile periods occur in bursts, which implies that the data is prone to volatility clustering. Evidence of this is found by for instance looking at the time of the financial crisis in 2008. The data also appears to be positively correlated with its closest previous period.

Table I – Descriptive Statistics of Log Returns

	Argentina	Brazil	England	France	Germany	Italy	Spain	WMP
Start Date	08.01.90	11.07.94	09.01.73	09.01.73	09.01.73	09.01.73	09.03.87	09.01.73
End Date	01.08.16	01.08.16	01.08.16	01.08.16	01.08.16	01.08.16	01.08.16	01.08.16
Mean	0,00174	0,00043	0,00028	0,00028	0,00020	0,00025	0,00019	0,00022
Median	0,00006	0,00000	0,00029	0,00015	0,00025	0,00000	0,00029	0,00050
Std. Dev	0,027	0,016	0,011	0,012	0,011	0,014	0,013	0,009
Maximum	0,376	0,195	0,091	0,099	0,160	0,105	0,117	0,091
Minimum	-0,608	-0,106	-0,130	-0,099	-0,121	-0,113	-0,114	-0,104
Skewness	0,245	0,106	-0,231	-0,268	-0,240	-0,276	-0,264	-0,512
Kurtosis	49,753	9,850	8,148	5,402	11,569	4,937	6,134	11,164
Jarque-Bera	783404	23855	31863	13935	67530	10673	12338	57622
Probability	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
N	7455	5760	11329	11329	11329	11329	7675	11329

In Table II we present a correlation matrix between all countries and the world market portfolio. The fact that international stock markets correlates across countries is highly evident, the returns in each country move in the same direction with correlations spanning from 0.307 between Argentina and Germany to a hefty 0.876 between England and France.

Table II – Correlation Matrix

	Argentina	Brazil	England	France	Germany	Italy	Spain	WMP
Argentina	■	0,456	0,316	0,313	0,307	0,307	0,321	0,080
Brazil	0,456	■	0,422	0,406	0,415	0,374	0,390	0,056
England	0,316	0,422	■	0,876	0,774	0,780	0,771	0,187
France	0,313	0,406	0,876	■	0,834	0,842	0,842	0,180
Germany	0,307	0,415	0,774	0,834	■	0,744	0,741	0,127
Italy	0,307	0,374	0,780	0,842	0,744	■	0,821	0,135
Spain	0,321	0,390	0,771	0,842	0,741	0,821	■	0,141
WMP	0,080	0,056	0,187	0,180	0,127	0,135	0,141	■

Note: The correlation matrix is constructed using data from the start date of the Brazilian index.

VI. Analysis

In this section, our outlined methodology is implemented on the given data set. The section is divided in three parts. In the first part we analyze the abnormal returns and comment our findings. In the second part we undertake a volatility analysis and the corresponding adjusted abnormal returns. In the third and final part, we present the asymmetry adjusted abnormal returns as a robustness check.

A. Abnormal Returns

We run equation 1 simultaneously for all countries by implementing country dummies, where the regression output indicates an adjusted R^2 of 18%. Table III presents the abnormal returns from our two approaches. Panel A describes the abnormal returns before the financial crisis using the start date of each index up until December 2007.

Table III – Results Abnormal Returns

	Single Event			Continuous Variable		
	Number of games	$\overline{AR}$	t-Values	Number of games	β	t-Values
Panel A: Before the financial crisis						
Wins	614	0,013	0,31	659	-0,012	-0,21
Losses	185	-0,188*	-1,84	193	-0,226**	-2,08
Panel B: After the financial crisis						
Wins	226	-0,069	-0,80	231	-0,051	-0,66
Losses	49	0,076	0,52	50	0,094	0,62
Panel C: Whole sample						
Wins	923	-0,025	-0,66	929	-0,025	-0,51
Losses	252	-0,127	-1,53	253	-0,144	-1,59

Note: *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

For our 185 observed losses, the point estimate from the single event approach indicate that the indexes experience a negative abnormal return of -18.8 basis points, statistically significant at the 10% level. The 614 wins before the financial crisis does not seem not have any effect on abnormal returns as it is not statistically different from zero.

The continuous variable approach, which replicates the study of Edmans et al. (2007), does not surprisingly result in a negative stock market reaction which is statistically significant at the 5% level. With data up until 2004, Edmans et al. (2007) reported an abnormal return of -21.2 basis points for all countries. Our analysis shows an abnormal return of -22.6 basis points with 193 observations.

From Panel A we can clearly reject our null hypothesis, and conclude that football matches indeed influence the stock markets and that there exists a loss effect before the financial crisis. Panel B presents the abnormal return generated after the financial crisis, from June 2009 until June 2016. In both approaches we can tell that none of the point estimates for wins and losses are statistically distinguishable from zero. Thus, we fail to reject the null hypothesis of football matches affecting the stock market after the financial crisis.

These results are consistent with theory on behavioral finance and it substantiates several findings from the literature review. Sentiments from football matches should not affect investors in order to maintain an efficient market. The behavioral finance theory suggest that investors are irrational and our findings from before the financial crisis demonstrates this. It appears that losses in football matches drive the mood, which in in turn drive the judgement. This is consistent with the findings of Lucey and Dowling (2005) who state that judgment is affected negatively from negative mood states.

However, the effect disappears after the financial crisis. From experimental markets we know that learning is a vital factor. One possible explanation could be that investors have learned to shield their judgment from these irrational sentiments. It could also be the case that investors are entering a more analytical mindset, as researched by Sinclair and Mark (1995), due to these negative feelings. An outcome of this is more rational choices, which in turn keeps the markets efficient. The findings are also similar to newer research, for example, Lee and Chiu (2016) concluded in their paper that investors no longer is affected from football sentiments.

B. Adjusted Abnormal Returns

The adjusted abnormal returns are based on normalizing all index returns and remove the effect of volatility. After estimating an ARMA(1,1) model for all indexes and checking for ARCH effects using the Engle and Ng test (1982), we can clearly reject the null hypothesis of no ARCH effects as both the F-statistic and Chi-Square are highly significant from Table IV. Thus, ARCH effects are present in all indexes.

Table IV – ARCH Effects

Indexes	F-statistic	Chi-Square	Prob. F	Prob. Chi-Square
Argentina	74,696	356,255	0,000	0,000
Brazil	106,202	487,648	0,000	0,000
England	547,663	2211,615	0,000	0,000
France	346,670	1506,531	0,000	0,000
Germany	220,902	1007,999	0,000	0,000
Italy	299,451	1325,028	0,000	0,000
Spain	173,116	779,848	0,000	0,000
WMP	654,627	2524,068	0,000	0,000

Note: Engle and Ng test (1982) for ARCH effects in the residuals on a ARMA(1,1) model for all countries, with five lags.

When ARCH effects are present, a GARCH model is deemed adequate. We estimate a GARCH(1,1) model for all countries and the WMP using the maximum likelihood technique, and we arrive at the following conditional variance equations:

$$\sigma_t^2{}_{Argentina} = 6.23 \cdot 10^{-6} + 0.1089 * u_{t-1}^2 + 0.8842 * \sigma_{t-1}^2$$

$$\sigma_t^2{}_{Brazil} = 4.45 \cdot 10^{-6} + 0.0890 * u_{t-1}^2 + 0.8918 * \sigma_{t-1}^2$$

$$\sigma_t^2{}_{England} = 1.61 \cdot 10^{-6} + 0.0967 * u_{t-1}^2 + 0.8896 * \sigma_{t-1}^2$$

$$\sigma_t^2{}_{France} = 3.37 \cdot 10^{-6} + 0.1022 * u_{t-1}^2 + 0.8732 * \sigma_{t-1}^2$$

$$\sigma_t^2{}_{Germany} = 1.66 \cdot 10^{-6} + 0.0938 * u_{t-1}^2 + 0.8932 * \sigma_{t-1}^2$$

$$\sigma_t^2{}_{Italy} = 3.23 \cdot 10^{-6} + 0.0841 * u_{t-1}^2 + 0.8992 * \sigma_{t-1}^2$$

$$\sigma_t^2{}_{Spain} = 2.88 \cdot 10^{-6} + 0.0982 * u_{t-1}^2 + 0.8850 * \sigma_{t-1}^2$$

$$\sigma_t^2{}_{WMP} = 1.15 \cdot 10^{-6} + 0.1016 * u_{t-1}^2 + 0.8841 * \sigma_{t-1}^2$$

First, we can conclude that both the ARCH and GARCH parameters are significant. The ARCH outputs appear to be quite low. Using England as example, the ARCH term states that 9.76% of yesterday's volatility affects new estimates. This makes sense as a total index will not suffer from the same short term shocks compared to a single stock. Looking at the GARCH coefficient α_2, this is usually found to be close to 0.9 in daily financial series (Brooks, 2014).

Again, by looking at England the GARCH term indicates that 88.96% of yesterdays estimated variance for today has an impact on today's estimated variance of tomorrow. The magnitude of $\alpha_1 + \alpha_2$ determines the speed of mean reversion. For all indexes, this measure is close to one which means that large volatility shocks use a longer period to decay. For this reason, we experience high persistence in the GARCH models. Also, these sums are not greater than one and this indicates that the GARCH models are stationary.

For stationary GARCH models, it is possible to discuss the unconditional variance of u_t, which is constant. It is given as (Bollerslev, 1986):

$$\sigma(u_t)_{England} = \sqrt{\frac{\alpha_0}{1-\alpha_1-\alpha_2}} = \frac{0.00000161}{1-0.0967-0.8896} = 0.0108$$

In addition, we compute the half-life shock present in the indexes:

$$England = \frac{1}{1-\alpha_1-\alpha_2} = \frac{1}{1-0.0967-0.8896} = 72.5584$$

The results tell us that the total return index for England has a daily volatility of 1.08% for the whole sample and shocks to the index will use approximately 73 days to half. For brevity we have only reported the results of England, but a similar analysis has been conducted on all indexes. For all countries we find that the average daily volatility is 1.43% and that shocks to the indexes of each country on average use 72 days to half.

After the estimation of each GARCH model, we normalize the returns with equation 4 and repeat the procedure for both approaches. Table V presents the adjusted abnormal returns.

Table V – Results Adjusted Abnormal Returns

	Single Event			Continuous Variable		
	Number of games	$\overline{AR}$	t-Values	Number of games	β	t-Values
Panel A: Before the financial crisis						
Wins	614	0,020	-0,48	659	-0,030	-0,55
Losses	185	-0,129	-1,27	193	-0,189**	-2,02
Panel B: After the financial crisis						
Wins	226	0,035	0,37	231	0,196	1,59
Losses	49	0,032	0,20	50	0,257	-1,37
Panel C: Whole sample						
Wins	923	0,018	0,46	929	0,013	0,27
Losses	252	-0,069	-0,81	253	-0,118	-1,41

Note: *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

First, notice the point estimates for the whole sample in Table V, Panel C. The coefficients for the loss events equal -0.07 and -0.12 for the single event and continuous variable approach respectively. This implies an average return that is 0.07 and 0.12 standard deviations below its mean. From the GARCH analysis the indexes have an average daily volatility of 1.43, which translates into an abnormal return of $0{,}07 * 1{,}43 \approx 0{,}11$ for the single event approach and $0.12 * 1{,}43 \approx 0.17$ for the continuous variable approach, which is almost identical to the point estimates for our abnormal results presented in Table III, Panel C.

Panel A in Table V presents the adjusted abnormal returns before the financial crisis. Before the GARCH adjustment, the single event approach indicated a statistically significant abnormal return after losses. However, for the adjusted abnormal returns we cannot reject our null hypothesis as none of the point estimates are statistically different from zero. The same is true for both Panel B and Panel C. The single event approach does not conclude with inefficient markets with respect to football sentiments, regardless of the timeframe.

Edmans et al. (2007) found with their continuous variable approach that the seven countries had an abnormal return of -21.7 basis points for losses, significant at the 5% level, after the GARCH adjustment. Our findings suggest a weaker loss effect of approximately -19.0 basis points significant at the 5% level, with 72 observations more than Edmans et al. (2007). Panel B and Panel C follow the same pattern as before the GARCH adjustment, the point estimates are not statistically significant at any conventional level.

The GARCH adjustment clearly has a greater effect on the single event approach compared with the continuous variable approach, where the former yielded insignificant results. One possible explanation for this is that we use 90 days to estimate our abnormal returns. We know from the volatility analysis that all the GARCH models are highly persistent, which means that volatility bursts occurring close to these 90 days will still affect the adjusted abnormal return at the day of the event. In addition, if volatility shocks occur at the start of the 90 days estimation period these will take 71 days on average to half. Hence, when we remove the effect of volatility using equation 4, we get more realistic results at any time *t*, indicating that investors are rational with regards to football sentiments.

Based on the analysis it is possible to argue that the estimation window of 90 days could be larger in order for the volatility bursts to have a lower influence on the abnormal returns before the GARCH adjustment. However, a larger estimation window also carries a downside as the overlap between estimation and event window will happen more frequently. A smaller event window does not seem reasonable as we want to capture the market movements before the event and based on research on event study methodology close to 100 days is considered as a minimum.

Lastly, we can tell that the continuous variable approach seems to overestimate the effect of sentiments, as the abnormal return coefficients are higher in contrast to the single event approach. A reason for this could be the fact that we use all historical data on the continuous variable approach which does not take into consideration the realistic aspect that is covered by the single event approach.

C. GJR Model

Estimating the GJR models is the robustness checks we conduct to verify our results. The GJR models take into account asymmetric shocks to the conditional variance. We ran equation 5 and found an outcome to the null hypothesis by using the Lagrange Multiplier test. From Table VI the Lagrange Multiplier scores and their corresponding *p*-values clearly reject the null hypothesis of no asymmetries for all indexes. With asymmetry present, the GJR extension is suitable.

Table VI – Lagrange Multiplier Test

Indexes	Lagrange Multiplier	Lagrange Multiplier *p*-value
Argentina	321,933	0,000
Brazil	374,284	0,000
England	874,543	0,000
France	439,536	0,000
Germany	475,936	0,000
Italy	546,880	0,000
Spain	342,036	0,000
WMP	949,917	0,000

Note: From equation 5, $TR^2 \sim \chi^2$ with 3 degrees of freedom with null hypothesis of no asymmetries.

From equation 6, we now have that the conditional variance equations are given as:

$$\sigma^2_{t\ Argentina} = 6.00 * 10^{-6} + 0.0973 * u^2_{t-1} + 0.8848 * \sigma^2_{t-1} + 0.0236 * u^2_{t-1} * I_{t-1}$$

$$\sigma^2_{t\ Brazil} = 4.93 * 10^{-6} + 0.0327 * u^2_{t-1} + 0.8993 * \sigma^2_{t-1} + 0.0875 * u^2_{t-1} * I_{t-1}$$

$$\sigma^2_{t\ England} = 1.55 * 10^{-6} + 0.0485 * u^2_{t-1} + 0.9031 * \sigma^2_{t-1} + 0.0696 * u^2_{t-1} * I_{t-1}$$

$$\sigma^2_{t\ France} = 3.68 * 10^{-6} + 0.0421 * u^2_{t-1} + 0.8810 * \sigma^2_{t-1} + 0.0938 * u^2_{t-1} * I_{t-1}$$

$$\sigma^2_{t\ Germany} = 1.93 * 10^{-6} + 0.0484 * u^2_{t-1} + 0.8949 * \sigma^2_{t-1} + 0.0785 * u^2_{t-1} * I_{t-1}$$

$$\sigma^2_{t\ Italy} = 3.12 * 10^{-6} + 0.0595 * u^2_{t-1} + 0.9026 * \sigma^2_{t-1} + 0.0413 * u^2_{t-1} * I_{t-1}$$

$$\sigma^2_{t\ Spain} = 2.80 * 10^{-6} + 0.0387 * u^2_{t-1} + 0.8968 * \sigma^2_{t-1} + 0.0894 * u^2_{t-1} * I_{t-1}$$

$$\sigma^2_{t\ WMP} = 1.51 * 10^{-6} + 0.0424 * u^2_{t-1} + 0.8773 * \sigma^2_{t-1} + 0.1152 * u^2_{t-1} * I_{t-1}$$

The GJR parameters γ are statistically significant, with coefficient values spanning from 0.0236 to 0.1152. Since it is the case that all indexes have $\gamma > 0$, we can conclude that negative shocks have a higher influence than the positives ones. Thus, there is evidence of asymmetry in volatility. Based on these findings it will be beneficial to use this GJR extension to our GARCH models since it takes into consideration the asymmetric shocks, which appear in our data. Table VII presents our findings.

Table VII – Robustness Check GJR Model

	Single Event			Continuous Variable		
	Number of games	$\overline{AR}$	t-Values	Number of games	β	t-Values
Panel A: Before the financial crisis						
Wins	614	0,079	0,31	659	0,034	0,39
Losses	185	0,114	-1,05	193	-0,064*	-1,77
Panel B: After the financial crisis						
Wins	226	0,179	0,66	231	0,061	0,40
Losses	49	0,039	-0,24	50	-0,130	-0,98
Panel C: Whole sample						
Wins	923	0,164	0,51	929	0,030	0,12
Losses	252	0,119	-0,90	253	0,056	-1,08

Note: *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

Panel A in Table VII presents the asymmetry adjusted abnormal returns before the financial crisis. As earlier, the single event approach does not appear statistically significant for neither wins nor losses. After the GJR adjustment we expect the coefficients to be lower than with the GARCH adjustment as the GJR term takes into consideration the magnitude of the asymmetric shocks to the conditional variance. This is the case for the continuous variable approach which indicates that stock markets drop by -6.4 basis points after losses. In contrast to earlier results, this point estimate is relatively low and only significant at the 10% level. Nevertheless, we can reject our null hypothesis and state that stock markets are affected by football sentiments.

Panel B describes the findings after the financial crisis, and as before, these results are not statistically distinguishable from zero. After this robustness check it is very clear that the effect football sentiments had before the financial crisis, does not exist anymore. Thus, we fail to reject the null hypothesis and we can say that markets are efficient with regards to football sentiments.

VII. Conclusion

Inspired by psychological evidence showing that sports have a strong effect on mood, this thesis has investigated the relationship between the sentiments from football results and the stock market. From the efficient market hypothesis there should not be any evidence of such a relationship, as markets are considered to be efficient and that stock prices reflect all available information. However, behavioral finance has enlightened the aspect of irrational investors who make decisions based on irrational information. We investigated this irrationality amongst investors using the national teams of Argentina, Brazil, England, France, Germany, Italy and Spain where we document a loss effect after football matches.

The analysis is conducted using two approaches within event study methodology, where the continuous variable approach is similar to Edmans et al. (2007) and the single event approach is an altered version where we use an estimation period to estimate expected returns. Emphasizing on the returns before the financial crisis, both approaches had results pointing towards irrational behavior amongst investors. Based on these findings it seems reasonable to conclude that the markets are inefficient with regards to football sentiments.

Like Edmans et al. (2007), we also created a normalized returns series, and adjusted for volatility. In doing so, the single event approach lost significance while the continuous variable remained statistically significant. From these results we can clearly tell how possible research biases occur. As both models carry their own flaws, it is hard to determine which model gives the most precise answer. One possible way to conclude is to say that both models need to show statistical significance. In this case we can clearly reject the null hypothesis and conclude that markets indeed are efficient.

However, if one of our approaches are highly robust, it could be stated that it is likely to be more precise. We implemented the GJR extension to our GARCH models to take into consideration the asymmetric shocks to the conditional variance. The continuous variable approach remained statistically significant, with an asymmetric adjusted abnormal return beta coefficient 16.2 basis points lower than the abnormal return coefficient. This high difference in point estimates tells that the abnormal return is exceedingly affected by asymmetry in volatility.

The continuous variable approach showed strong resilience to both the GARCH model and the GJR extension. The single event approach does not seem equally robust and if we relax the up and downside with each model, there definitely is a relationship between football results and stock returns with the continuous variable being so robust.

Throughout this thesis, we have also put emphasis on investor behavior after the financial crisis. None of the point estimates from both approaches are statistically significant, implying that the irrationality that existed before the crisis have disappeared. These findings make sense as bad mood states result in a more analytical investor (Sinclair & Mark, 1995).

Given that the results for the continuous variable approach are highly robust, we reject our null hypothesis and conclude that stock markets were affected by football sentiments and therefore not efficient, before the financial crisis. The returns after the financial crisis did not show any sign of being statistically significant and we thus failed to reject the null hypothesis. Hence, the markets are efficient with regards to football sentiments after the financial crisis.

A. Limitations and Future Research

One of the limitations in this thesis, and also a possible explanation to the decreasing significance after the financial crisis, is the number of foreign investors. We examine the effect of national teams in their respective countries and if the indexes in these countries are heavily influenced by foreign investors, we could be in danger of not capturing the real effect as they are indifferent to the results. Thus, one proposition for future research is to base the analysis on small and local firms which potentially have a lower number of foreign investors (Edmans et al., 2007).

Another aspect not considered in this thesis is the implementation of expectation. Markman and Hirt (2002) state that individuals who are psychologically invested in a desired outcome generate biased predictions. Supporters form expectation to each game and if it is the case that they expect their team to win, then one possible hypothesis is that the stock market reaction is greater after losses than after wins.

A necessity to draw statistical conclusions is to have a respectable number of observations. Edmans et al. (2007) investigated how different match types affected the stock market. As previously discussed, this requires enough data and since we have limited our thesis to seven countries, this method becomes a problem in terms of observations. The different match types are relevant to consider as elimination games often carries more weight than a qualifying game. For instance, a country can already be qualified when they play their last game in the qualifying group and it is reasonable to believe that such matches are of less importance to supporters. Thus, future research should focus on the time after the financial crisis as more data becomes available and it becomes easier to investigate the different types of matches.

References

Adesina, T. (2017). Estimating volatility persistence under a Brexit-vote structural break. *Finance Research Letters*.

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

Armitage, S. (1995). Event study methods and evidence on their performance. *Journal of Economic Surveys*, *9*(1), 25-52.

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

Barber, B. M., & Lyon, J. D. (1997). Detecting long-run abnormal stock returns: The empirical power and specification of test statistics. *Journal of financial economics*, *43*(3), 341-372.

Beck, N., & Katz, J. N. (1995). What to do (and not to do) with time-series cross-section data. *American political science review*, *89*(3), 634-647.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of econometrics*, *31*(3), 307-327.

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

Brooks, C. (2014). *Introductory econometrics for finance*. Cambridge University Press.

Brown, S. J., & Warner, J.B. (1980). Measuring security price performance. *Journal of Financial Economics*, *8*(3), 205-258

Cao, M., & Wei, J. (2005). Stock market returns: A note on temperature anomaly. *Journal of Banking & Finance*, *29*(6), 1559-1573.

Corrado, C. J. (2011). Event studies: A methodology review. *Accounting & Finance*, *51*(1), 207-234.

Dahlquist, M., & Robertsson, G. (2001). Direct foreign ownership, institutional investors, and firm characteristics. *Journal of financial economics*, *59*(3), 413-440.

De Long, J. B., Shleifer, A., Summers, L. H., & Waldman, R. J. (1990). Positive feedback investment strategies and destabilizing rational speculation. *the Journal of Finance*, *45*(2), 379-395.

Dufwenberg, M., Lindqvist, T., & Moore, E. (2005). Bubbles and experience: An experiment. *The American Economic Review*, *95*(5), 1731-1737.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the Econometric Society*, 987-1007.

Engle, R. F., & Ng, V. K. (1993). Measuring and testing the impact of news on volatility. *The journal of finance*, *48*(5), 1749-1778.

Fama, E. F. (1965). The behavior of stock-market prices. *The journal of Business*, *38*(1), 34-105.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The journal of Finance*, *25*(2), 383-417.

Forgas, J. P. (1995). Mood and judgment: the affect infusion model (AIM). *Psychological bulletin*, *117*(1), 39.

French, K. R., Schwert, G. W., & Stambaugh, R. F. (1987). Expected stock returns and volatility. *Journal of financial Economics*, *19*(1), 3-29.

Frieder, L., & Subrahmanyam, A. (2004). Nonsecular regularities in returns and volume. *Financial Analysts Journal*, 29-34.

Gibbons, M. R., & Hess, P. (1981). Day of the week effects and asset returns. *Journal of Business*, 579-596.

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The journal of finance*, *48*(5), 1779-1801.

Gorton, G. B. (2010). *Questions and answers about the financial crisis* (No. w15787). National Bureau of Economic Research.

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

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

Hoffmann, A. O., Post, T., & Pennings, J. M. (2013). Individual investor perceptions and behavior during the financial crisis. *Journal of Banking & Finance*, *37*(1), 60-74.

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

Kahneman, D., & Tversky, A. (1986). Rational choice and the framing of decisions. *The Journal of Business*, S251-S278.

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

Kaustia, M., & Rantapuska, E. (2016). Does mood affect trading behavior?. *Journal of Financial Markets*, 29, 1-26.

Kendall, M. G. (1953). The Analysis of Economic Time-Series – Part 1: Prices. *Journal of the Royal Statistical Society. Series A (General)*, *116*(1), 11-34.

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

Lee, J. S., & Chiu, C. W. (2016). Sport Sentiments and Stock Returns: Example of FIFA World Cups. *Applied Economics and Finance*, *4*(2), 44-56.

Loewenstein, G. F., Weber, E. U., Hsee, C. K., & Welch, N. (2001). Risk as feelings. *Psychological bulletin*, *127*(2), 267.

Lo, A. W. (2005). Reconciling efficient markets with behavioral finance: the adaptive markets hypothesis. *Journal of Investment Consulting*, *7*(2), 21-44.

Lucey, B. M., & Dowling, M. (2005). The role of feelings in investor decision-making. *Journal of economic surveys*, *19*(2), 211-237.

Lucey, B. M., & Dowling, M. (2008). Robust global mood influences in equity pricing. *Journal of Multinational Financial Management*, *18*(2), 145-164.

MacKinlay, A. C. (1997). Event studies in economics and finance. *Journal of economic literature*, *35*(1), 13-39.

Markman, K. D., & Hirt, E. R. (2002). Social prediction and the "allegiance bias". *Social Cognition*, *20*(1), 58-86.

Noussair, C., Plott, C., & Riezman, R. (2007). Production, trade, prices, exchange rates and equilibration in large experimental economies. *European Economic Review*, *51*(1), 49-76.

Rozeff, M. S., & Kinney, W. R. (1976). Capital market seasonality: The case of stock returns. *Journal of financial economics*, *3*(4), 379-402.

Schwarz, N. (1989). Feelings as information: Informational and motivational functions of affective states.

Schwarz, N., & Clore, G. L. (1983). Mood, misattribution, and judgments of well-being: Informative and directive functions of affective states. *Journal of personality and social psychology*, *45*(3), 513.

Schwarz, N., & Clore, G. L. (2003). Mood as information: 20 years later. *Psychological Inquiry*, *14*(3-4), 296-303.

Schwert, G. W. (2003). Anomalies and market efficiency. *Handbook of the Economics of Finance*, *1*, 939-974.

Shiller, R. J. (2003). From efficient markets theory to behavioral finance. *The Journal of Economic Perspectives*, *17*(1), 83-104.

Sinclair, R. C., & Mark, M. M. (1995). The effects of mood state on judgemental accuracy: Processing strategy as a mechanism. *Cognition & Emotion*, *9*(5), 417-438.

Tukey, J. W. (1977). Exploratory data analysis. Reading, PA: Addison-Wesley.

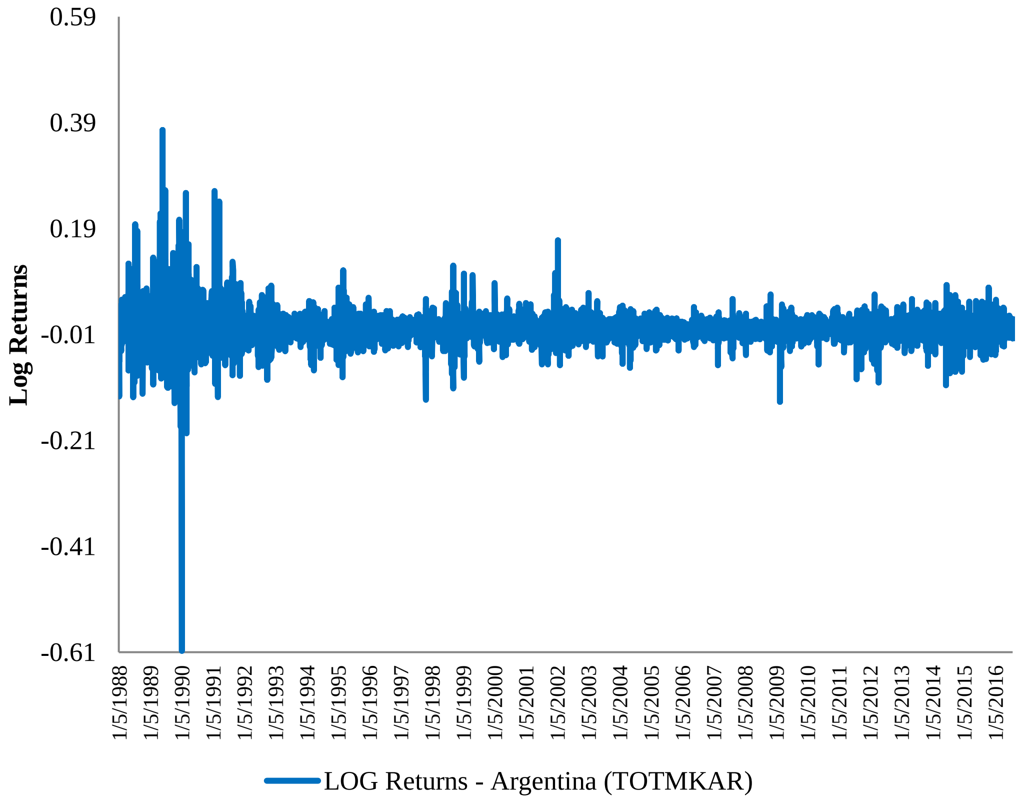
Wachtel, S. B. (1942). Certain observations on seasonal movements in stock prices. *The journal of business of the University of Chicago*, *15*(2), 184-193.

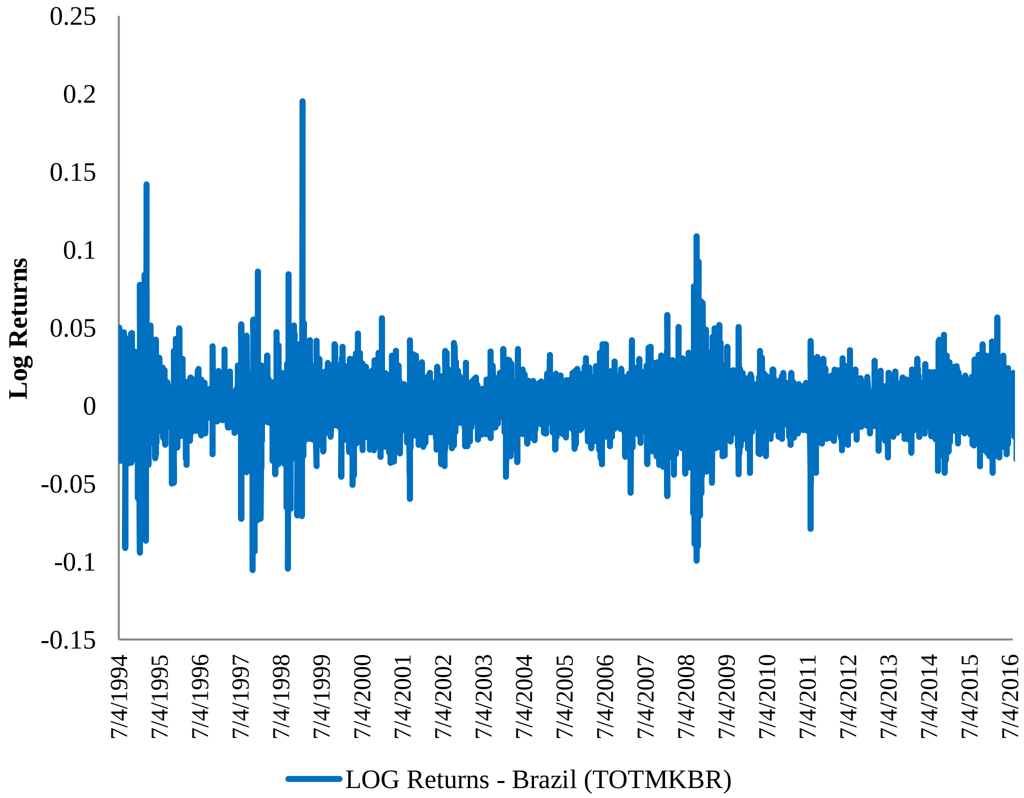
Wright, W. F., & Bower, G. H. (1992). Mood effects on subjective probability assessment. *Organizational behavior and human decision processes*, 52(2), 276-291.

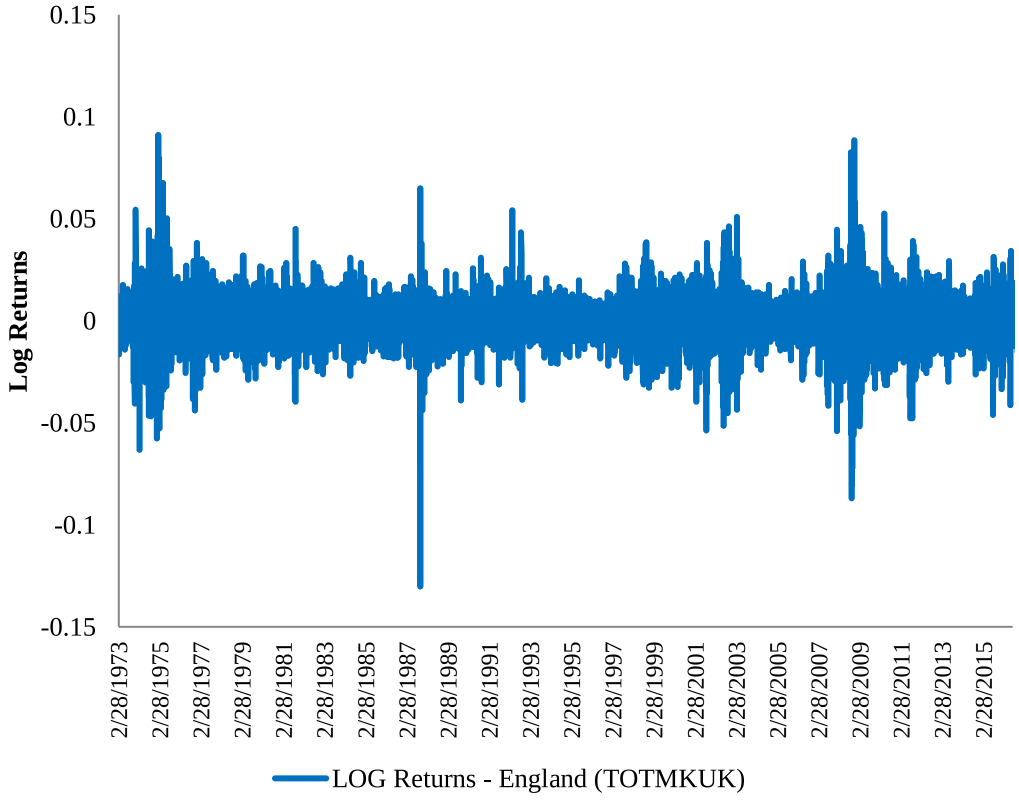
Yuan, K., Zheng, L., & Zhu, Q. (2006). Are investors moonstruck? Lunar phases and stock returns. *Journal of Empirical Finance*, *13*(1), 1-23.

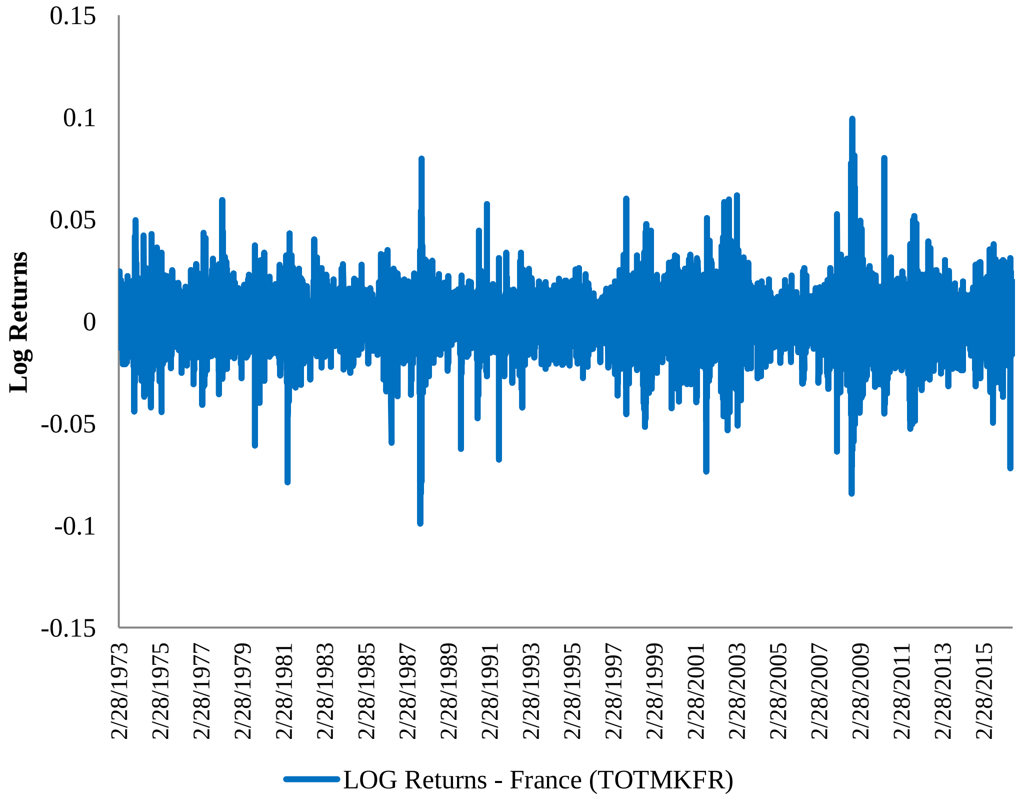
Appendix

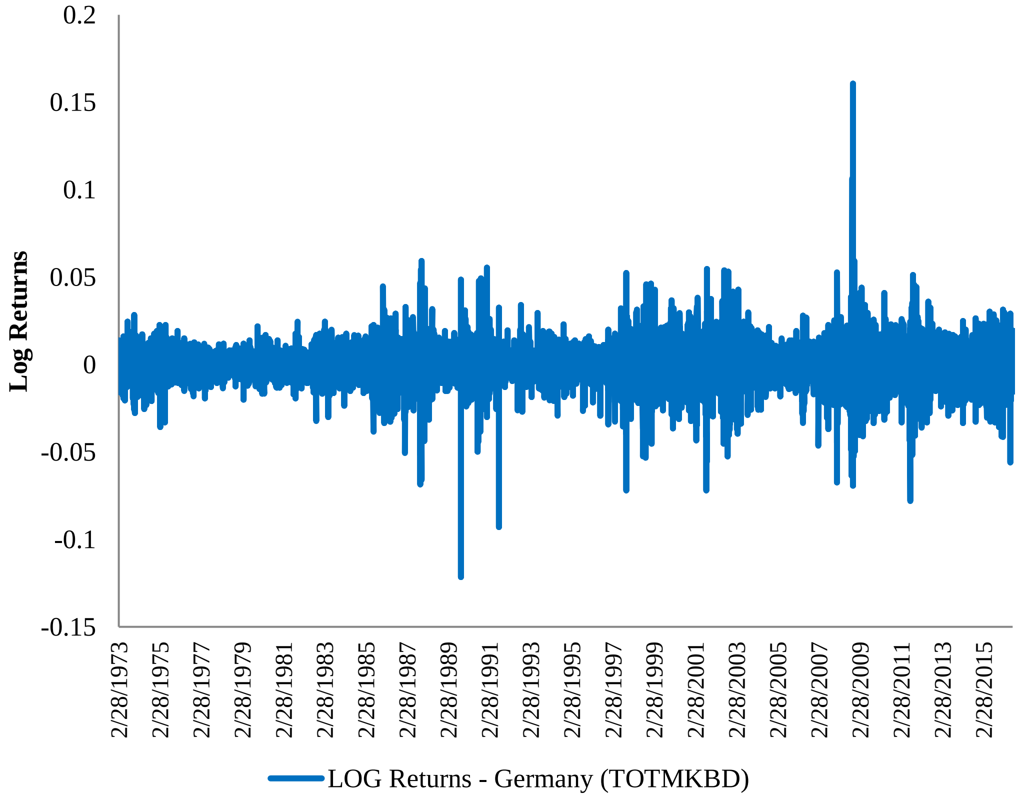
Appendix 1 – Graph of Log Returns

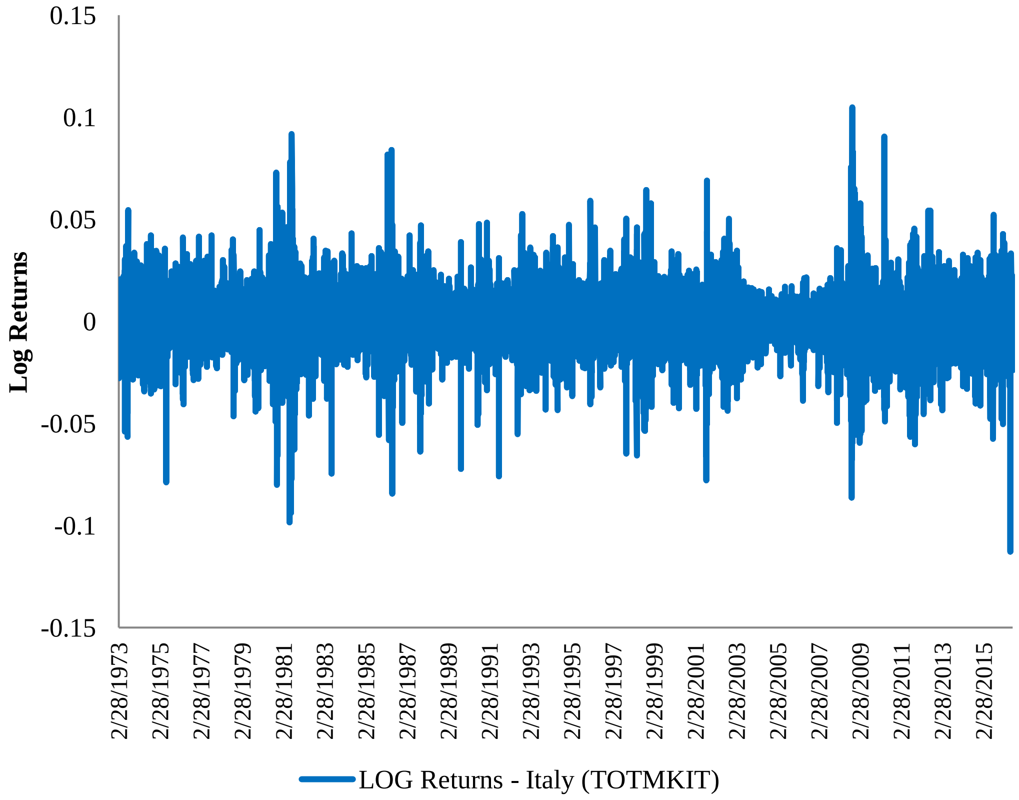


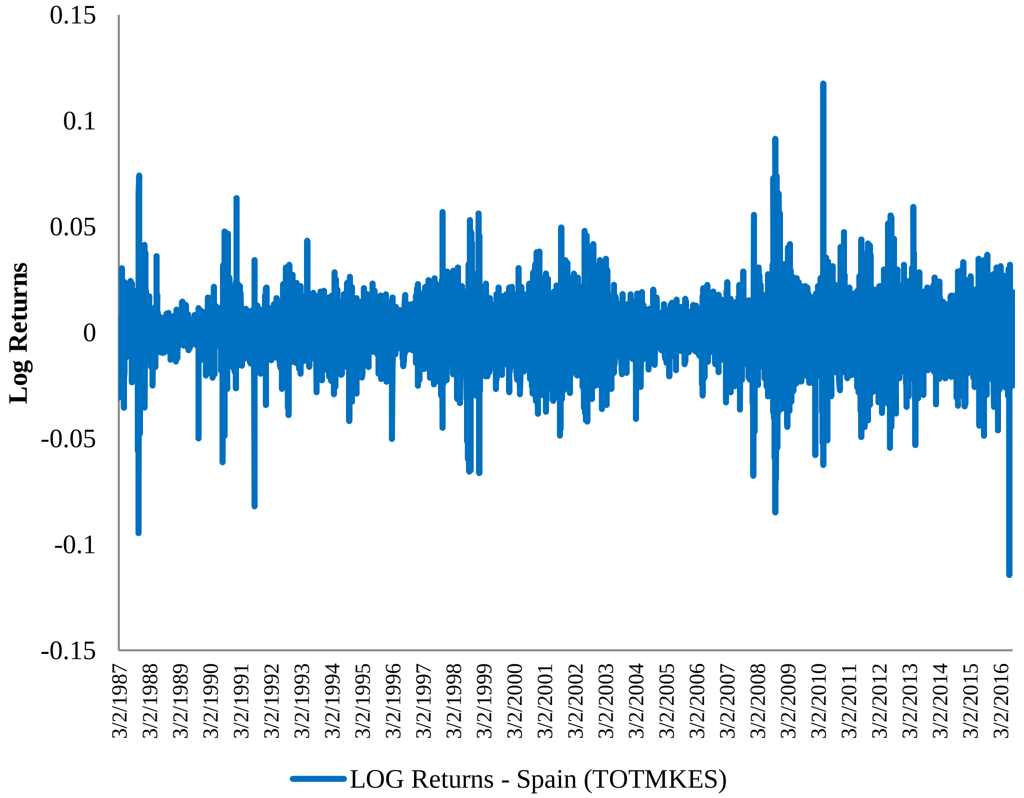



0.15
0.1
0.05
0
-0.05
-0.1
-0.15
Log Returns
2/28/1973
2/28/1975
2/28/1977
2/28/1979
2/28/1981
2/28/1983
2/28/1985
2/28/1987
2/28/1989
2/28/1991
2/28/1993
2/28/1995
2/28/1997
2/28/1999
2/28/2001
2/28/2003
2/28/2005
2/28/2007
2/28/2009
2/28/2011
2/28/2013
2/28/2015
LOG Returns - England (TOTMKUK)


0.15
0.1
0.05
0
-0.05
-0.1
-0.15
Log Returns
2/28/1973
2/28/1975
2/28/1977
2/28/1979
2/28/1981
2/28/1983
2/28/1985
2/28/1987
2/28/1989
2/28/1991
2/28/1993
2/28/1995
2/28/1997
2/28/1999
2/28/2001
2/28/2003
2/28/2005
2/28/2007
2/28/2009
2/28/2011
2/28/2013
2/28/2015
LOG Returns - France (TOTMKFR)


0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
Log Returns
2/28/1973
2/28/1975
2/28/1977
2/28/1979
2/28/1981
2/28/1983
2/28/1985
2/28/1987
2/28/1989
2/28/1991
2/28/1993
2/28/1995
2/28/1997
2/28/1999
2/28/2001
2/28/2003
2/28/2005
2/28/2007
2/28/2009
2/28/2011
2/28/2013
2/28/2015
LOG Returns - Germany (TOTMKBD)


0.15
0.1
0.05
0
-0.05
-0.1
-0.15
Log Returns
2/28/1973
2/28/1975
2/28/1977
2/28/1979
2/28/1981
2/28/1983
2/28/1985
2/28/1987
2/28/1989
2/28/1991
2/28/1993
2/28/1995
2/28/1997
2/28/1999
2/28/2001
2/28/2003
2/28/2005
2/28/2007
2/28/2009
2/28/2011
2/28/2013
2/28/2015
LOG Returns - Italy (TOTMKIT)



Appendix 2 – Whole Sample Volatility Analysis

	ARCH + GARCH	Daily volatility	Half-life shock
Argentina	0,9929	0,0297	142
Brazil	0,9808	0,0152	52
England	0,9862	0,0108	73
France	0,9754	0,0117	41
Germany	0,9871	0,0113	77
Italy	0,9833	0,0139	60
Spain	0,9831	0,0131	59
WMP	0,9858	0,0090	70
	Average	1,43%	72

Note: Daily volatility and half-life shock are based on the unconditional variance analysis by Bollerslev (1986).