Erasmus University Rotterdam

Behavioural Economics Section

Master Thesis

Irrationality in Emerging and Developed Markets

Investigation of the relationship between irrational trading behavior and the level of market development

Abstract

The goal of this thesis is to obtain a clearer view on country or market specific characteristics that explain irrational trading behavior induced by sentiment from international soccer matches. Motivated by existing studies that found a link between investor mood and stock returns, this paper provides more insight into the relationship between irrational trading behavior and the development level of the financial markets. The topic is investigated with different methodological approaches. None of the used methods revealed a significant relationship between the level of market development and irrational trading behavior. To put this negative result into perspective, the robustness of previous findings is also investigated at the end of the paper.

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Introduction

In the traditional finance paradigm the Efficient Market theory was the key proposition in explaining financial markets for many years. An efficient market is defined as a market in which prices always "fully reflect" all available information (Fama, 1970; Fama, 1991). The Efficient Market Hypothesis (EMH) holds when financial markets always reflect the fundamental value of assets, meaning there are no mispricings in the market. However, during the early 90s a new paradigm emerged with the main idea that financial markets are comprised of human beings that make mistakes and do not always behave rationally. This was the beginning of the new behavioral finance paradigm. In the new paradigm market (in)efficiency is investigated through the behavior of market participants rather the availability of information in financial markets. Contrarian to traditional finance, agents in behavioral finance models are not fully rational. They can make choices that are normatively unacceptable. Furthermore, agents fail to consequently update their beliefs correctly, meaning prices do not always incorporate all available information and misvaluations can occur (Barbaris & Thaler, 2003).

During the last two decades, an increasing number of studies used a behavioral approach in explaining stock price movements in financial markets. A study by Edmans, Garcia and Norli (2007) investigated stock market reactions to sudden changes in investor mood (investor sentiment) induced from international soccer matches. The authors found a negative effect on local stock markets after a country lost a match, which they call the *loss effect*. This negative effect on stock returns can be seen as a form of irrational behavior of investors, given that their investment decisions were biased by presumably unrelated events. Later on, Kaplanski and Levy (2010) analyzed the exploitability of irrational behavior that was explained by sentiment induced from FIFA World Cups. They found an exploitable aggregate negative effect on the US stock market. The effect was explained by multiple negative local market effects, spilling over from all losing country indices to the US stock market during FIFA World Cup tournaments.

More recent literature focusses on irrationality in less developed markets. Investor sentiment is found to be a key variable in the prices of stocks traded in three emerging Central European countries: Hungary, Poland and the Czech Republic (Corredor, Ferrer, & Santamaria, 2015). Furthermore, the study shows that investor sentiment in these emerging markets has stronger impact on the stock prices than in developed markets in Europe. Another finding is that emerging markets are less efficient and in general experience more frequent price deviations (Lim & Brooks, 2011). Earlier research on irrationality in emerging markets presented evidence that investors in China exhibit behavioral biases and make poor investment decisions (Chen, Kim, Nofsinger, & Rui, 2004).

Whereas the effect of investor sentiment on stock returns has been widely researched, there is little research on this effect in developing markets as opposed to developed markets. This research paper aims to contribute to the existing literature by investigating this matter from multiple angles.

The structure is as follows. The research question and hypotheses are discussed in the first section in order to get a clear focus of my research goal and structure. In the following section I present a literature review. This section contains relevant academic papers to the topic and provides more theoretical background for my main research question and hypothesis. Section 3 elaborates on the first approach towards answering my main research question. The next section describes the second approach that is used to answer the main question of this paper. Both sections 3 and 4 contain subsection that elaborate on the data, method and results. In section 5 the results of my paper are discussed and proposals for future research are made. The conclusion is presented in section 6.

1 Research question and hypotheses

The literature discussed in the introduction serves as a foundation for my research question and the methodology I use towards testing my hypotheses. The main research question of my paper is:

> *Is the irrationality caused by investor sentiment larger in less developed markets than in more mature markets?*

A tricky part of this question is that the level of market development/maturity is an unobservable construct. In other words, it is not a variable that is directly observable. In order to capture the most accurate level of market development/maturity, relevant observable aspects of this construct have to be taken into account. Since the selection of these aspects is subjective, it is challenging to investigate this research question.

To answer the research question, I develop two types of methodology. The first method is the *aggregate market method*. In this method FIFA World Cup match days serve as variables that capture investor sentiment and Global Equity Indices are used to compare the effect in developing and developed markets. It extends on the methodology of Kaplanski and Levy (2010) who showed a negative impact on the US stock market that was explained by negative market sentiment induced from all loosing countries in a FIFA tournament. The methodology uses regressions with GARCH adjusted returns and is further discussed in section 3.2. The effect of the aggregate market method is referred to as the *aggregate loss effect*. Several research papers indicated that there is more irrationality among investors in less developed markets. Therefore, I expect the aggregate loss effect on stock markets to be more negative in less developed markets. The following hypothesis is used in the aggregated market method:

> *H1: The aggregate loss effect is stronger in less developed markets than in more mature markets.*

The second method I build to answer my main research question focuses more on the construction of variables that capture the level of market development/maturity. By constructing five different proxies for the level of market development/market maturity, the irrationality in different stock markets is investigated. I call this method the *local market method.* In this method, match days of multiple FIFA tournaments are used to capture market sentiment. The method extents on a study of Edmans, Garcia and Norli (2007), who investigated irrational trading behavior on different local stock markets. In their method the authors estimate panel regressions on GARCH adjusted returns using panel corrected standard errors (PCSE) in order to investigate this relation. The details of the extended method are discussed in section 4.2. Since Edmans, Garcia and Norli (2007) only found a negative impact on local stock markets after FIFA soccer matches were lost, I only analyze the effect after soccer matches were lost. The effect of the local market method I call the *local market loss effect*. The hypothesis constructed for this method is:

> *H2: The local market loss effect is stronger in less developed markets than in more mature markets.*

The second hypothesis is tested using the proxies for market development as dummy variables (section 4.2.2) and as continuous variables (section 4.2.3). The five proxies that are used for the analyses are: *HDI, market type, GDP, volatility* and *liquidity* (section 4.1.2).

2 Literature review

2.1 Investor sentiment and stock returns

Human emotions and mood play an important role in the irrationality of people. Numerous psychological studies showed that individuals' feelings influence their decision-making. Generally people who are in a good mood are more optimistic in their choices, leading to a decreased risk perception. On the other hand, when people are in a bad mood they are more pessimistic in their choices, leading to an increased risk perception (Johnson & Tversky, 1983; Petty, Gleicher, Baker, 1991; Loewenstein, Weber, Hsee & Welch, 2001; Dowling & Lucey, 2004). For many economists these predictions were a good reason to investigate how investors in financial markets form their beliefs. Based on psychological evidence Barbaris, Shleifer and Vishny (1998) presented a model of investor sentiment, or on how investors form beliefs, that produced both overreaction and underreaction for a wide range of parameters. In general, investor sentiment refers to investors' opinions regarding future cash flows and investment risk.

Many studies investigated the effect of investor sentiment on stock prices in financial markets caused by several presumptively unrelated factors. The weather, having an effect on peoples' mood, seemed to be correlated with stock returns. Both the amount of sunlight and temperature showed significant influence on stock market returns (Saunders, 1993; Hirshleifer & Shumway, 2003; Cao & Wei, 2005). Furthermore, it was found that the presence of seasonal affective disorder, also known as a seasonal depression, has an effect on stock market returns around the world (Kamstra, Kramer & Levi, 2003). Even a relation between lunar phases and stock market returns was found (Yuan, Zheng & Zhu, 2006). More recently, a study supported evidence for a relation between TV series finales and stock returns in the US stock markets (Lepori, 2015). Derived from the fact that popular TV series finales cause negative emotional reactions amongst many viewers, the author finds that an increase in the fraction of Americans watching a TV show finale is followed by a decrease in US stock returns. Furthermore, during periods of Ramadan stock return were found to be significantly higher in several Muslim countries. Ramadan, promoting feeling of solidarity among Muslims, positively influences investor psychology leading to optimistic beliefs about investment decisions (Bialkowsky, Etebari & Wisniewsky, 2012).

2.2 Soccer as investor sentiment proxy

The previous studies demonstrated that several events created market sentiment that significantly influenced stock prices, with positive market sentiment leading to higher prices and vice versa. Another mood proxy often used as a measure for investor sentiment is sports. Psychological evidence shows that the outcome of sports events influences the emotional state of sport fans. According to Wann et al. fans experience a strong negative reaction after a loss of their team and a corresponding positive reaction after their team wins. Moreover, these reactions lead to positive or negative feelings about life in general (Wann, Dolan, McGeorge & Allison 1994). Sports can even influence people beyond simple changes in mood. A research paper by Wann (2001) documented an increase in riots after a loss of sports teams in particular cities. Dutch researchers found an increase in mortality from coronary heart disease and stroke caused by the stress of important soccer matches during the 1996 European Championship (Witte, Bots, Hoes & Grobbee, 2000). Given the fact that sports results cause negative and positive feelings amongst people in general, one can hypothesize that these emotions can affect investors' trading behavior.

While many papers show that sports in general affect human behavior, soccer in particular is one of few sports that is perfectly suitable for an analysis on the effect of investor sentiment on stock returns at a regional and country level. According to Edmans, Garcia and Norli (2007), it satisfies the most important characteristics of a mood variable: soccer drives peoples' mood, it impacts the mood of a large proportion of a population and the mood effect is correlated across individuals in a region or country. Moreover, soccer is one of the most popular sports in world. Soccer is being played across 150 countries in the world by over 250 million people. The aggregate number of in home television spectators of the 2010 and 2014 FIFA World Cup reached over 3.2 billion people, which is 46.4% of the global population[1]. Moreover, in the 2014 FIFA World Cup, over 40 billion impressions of digital content about the world cup were measured during the tournament[2].

In 2003, researchers found a strong relation between the performance of the national soccer team of England and subsequent daily stock returns in the national index (Ashton, Gerrard & Hudson, 2003). Some years later, Klein, Zwergel and Heiden (2009) published a critical article with results contrary to those of the original paper by Ashton, Gerrard & Hudson (2003) and supporting market efficiency. Using the same data, they found no significant relation between soccer match results and national stock index

[1] FIFA 2010 report: http://www.fifa.com
[2] **FIFA 2014 report: http://www.fifa.com**

returns (Klein, Zwergel & Heiden, 2009). In turn, the writers of the original paper critically reviewed the interpretation of the results by Klein et al. They argued their results had a strong bias towards wishing to show market efficiency (Ashton, Gerrard & Hudson 2011). By reexamining the relation between national soccer outcomes and stock returns, they indeed showed there was still an effect. However, after extending their original data set to include more years, it was reported that the effect of soccer games on stock index returns declined over this period.

Edmans et al. were one of the first researchers linking sports, soccer in particular, to investor sentiment in a cross-country analysis (Edmans, Garci & Norli, 2007). As mentioned in the introduction, they only found a significant decreased return on local stock markets after a country had lost a match. No significant effect had been found after matches had been won. The found loss effect is consistent with the loss aversion bias that refers to the fact that losses loom larger than wins (Kahneman & Tversky, 1979). Another behavioral bias that is related the effect of investor sentiment on local stock market is the home bias (Tesar & Werner, 1995). The home bias is the tendency of investor to invest in domestic stocks.

Kaplanski and Levi (2010) investigated the aggregate effect of World Cup sentiment on a single market. As mentioned in the introduction they find an aggregate negative effect that is long lasting and exploitable. Contrary to other papers, their aggregate affect doesn't depend on the results of the soccer matches. From the understanding that in the FIFA World Cup tournament all but one team eventually loose, a negative sentiment spills over from several local markets to the US stock exchange. The authors claim the sentiment spills over due to global integration of markets and foreign investors that are active in the US stock market. Years later, the same authors show that after they published their paper in 2010, the sentiment effect changed. They presumed this change was explained due to investors that had exploited the effect after 2010, restoring market efficiency. Although the abnormal returns were still available, they showed a decline in the aggregate negative sentiment effect after 2010 (Kaplanski & Levy, 2014). More recently, a study by Kang and Park (2015) also found that exploiting the sentiment effect from national soccer matches in the Korean market is not worthwhile due to the short lived window of opportunity and insufficient financial benefit.

The literature discussed in section 2.1 and 2.3 provide enough evidence for the assumption that emotions induced by different events, soccer in particular, can affect investor sentiment. Consequently, investor sentiment proved to be influencing the trading behavior of investors. These assumptions underpin the use of soccer matches in order to capture irrational trading behavior in my research.

2.3 Drivers of irrationality

An increasing number of papers have been written about different market characteristics and their sensitivity to investor sentiment. When investors are influenced by market sentiment, market sentiment can be followed by irrational trading behavior in these markets. On the other hand, when (sophisticated) investors try to correct for mispricings, markets become more efficient. As mentioned earlier, the more efficient capital markets are, the better they reflect the fundamental value of assets. Are there characteristic of equity markets that attract noise traders that are fueling irrationality in these particular markets?

In a cross-country analysis Lim and Brooks (2010) found that stock markets in economies with a lower GDP per capita generally experience more frequent price deviations than those in economies with a higher average income group. They argue these markets are dominated by sentiment-prone noise traders, causing asset prices in emerging markets to deviate from the fundamental value. (Lim& Brooks, 2010). From the results of this study, one can state that markets characterized by low GDP per capita and high volatility are less efficient due to the presence of noise traders. Hence, there could be reason to believe that the irrationality in markets with these characteristics is stronger.

Another study investigates whether more integrated stock markets are associated with higher levels of informational efficiency. Market integration in this context refers to the extent to which stock markets are closely linked together in terms of information sharing, technology and foreign investors. Analyzing data from 49 countries, they found robust evidence for a positive relation between stock market integration and market efficiency (Hooy & Lim, 2013). Generally, developed markets are more integrated than developing markets. Given the relation between market integration and market efficiency found by Hooy & Lim (2013), could this also mean that investors in developed markets are more rational than investors in developing markets?

A paper by Schmeling (2009) investigated individual investor mood (sentiment) in different country and market specific characteristics, which in turn caused negatively affected future stock returns. By creating a proxy for investor sentiment, they showed that high market sentiment is related to lower expected future stock returns and vice versa. They found that the effect was more pronounced for countries that had less market integrity and less efficient regulatory institutions. Also volatile markets with stocks that are difficult to value were more prone to sentiment effects (Schmeling, 2009). The fact that volatile markets are more prone to sentiment effects is in line with the findings of the earlier discussed research of Lim and Brooks (2010).

Bekaert and Harvey (2007) use some of the discussed characteristics to distinguish emerging from developed equity markets. They argue that emerging markets generally have lower average returns, are less volatile and often less liquid. Recent research on irrationality in emerging markets showed existence of an overreaction effect on financial stock markets in periods of fear and stress in financial (Viebig, 2015).

In the literature review in this subsection, many of the market specific characteristics that were related to irrationality on stock markets reflect aspects of emerging and developed markets. Different studies provide evidence that underpins irrationality is more pronounced in markets with characteristics of emerging markets. These findings can be seen as the foundation of my main research question and hypotheses.

3 The aggregate market model

This section extends the approach of Kaplanski and Levy (2010) by comparing the impact of market sentiment on stock returns in emerging and developed markets. In the paper this method is referred to as the “aggregate market method”. Four Datastream Global Equity indices are used to construct two panels, each consisting of one index reflecting emerging markets and one index reflecting developed markets. Both panels are estimated separately with panel regressions on GARCH adjusted returns. The method compares the impact of sentiment during FIFA World Cup tournament days.

3.1 Data

3.1.1 Financial data

For the aggregate market method, four Datastream Global Equity indices were downloaded from DataStream in order to construct two panels. These global equity indices are produced by aggregating market indices with the same characteristics or from the same geographical region. The indices provide a detailed overview of global and regional markets. The Global Equity Indices form a comprehensive, independent standard for equity research and benchmarking. I constructed a *global panel* that consists of two global equity indices representing emerging and developed markets. I also constructed a *continental panel,* for which I used two regional indices representing European and Latin American markets. The main reason to use the regional indices of Europe and Latin America is that these continents are known to be very fanatic soccer regions. All top seven soccer nations are located in these continents: Argentina, Brazil, England, France, Germany, Italy and Spain[3]. As a result I have two panels consisting of two indices, one representing developed markets and one representing less developed markets. The global and continental panels have 16176 and 16306 trading days respectively. More details on these indices can be found in appendix 1. In order to replicate the original method of Kaplanksi & Levy (2010), a third dataset is constructed with only the total return index of the US stock market. This index contains 8835 trading days and is downloaded from Datastream as well.

[3] According to Edmans, Garcia and Norli (2007), the professional soccer leagues of all European countries account for 80% of all soccer revenues in the European continent. Together with the two South American countries, these seven soccer nations systematically represent the top world rankings.

3.1.2 Soccer data

To measure the sentiment effects, all FIFA World Cup match days are used in the both panels starting from the 1974 World Cup until the 2014 World Cup. The World Cup data was downloaded from http://www.flashscore.com and the results were double checked with the official FIFA website. Due to different starting dates not all available match day observations were included in the indices. In total 299 and 307 World Cup match days were used in the global and continental panels. The data used for replication had 153 World Cup days.

Overall, FIFA international soccer tournaments have been using the same format. However, the rules and the number of contestants have changed slightly over the last 40 years. There is a qualifying round for each end tournament. In this stage, national soccer teams from different geographic regions are divided into groups to play each other in order to earn a ticket for the end tournament. Only the best two teams of each group got a ticket. From 1996 onwards, wild cards for the end tournament are earned in qualification finals matches that take place at the end of the qualification period. Two countries are playing each other twice in order to win the final tickets to the end tournament. After this round all competing countries for a tournament are fixed. Every end tournament begins with a group round in which teams are divided into groups of 3 or 4. After the group stage, elimination games are played in a knock out system with 8th finals, quarterfinals, semifinals and eventually the final. The later the stage in the tournament, the more important the matches become. To be sure to analyze only important games, I decided to analyze only all end tournament matches and the qualification finals matches.

3.2 The aggregate market method

3.2.1 The model

For the aggregate market method, the following model is used. In the model, several control variables are used to account for market anomalies that in the past have proven to explain some part of the behavior of stock returns (Jacobs & Levy, 1988).

$$R_{it} = \gamma_0 + \gamma_1 R_{it-1} + \gamma_2 R_{it-2} + \gamma_3 D_t + \gamma_4 H_t + \gamma_5 T_t + \gamma_6 P_t + \gamma_{6i} J_{it} + \gamma_8 EED + \varepsilon_{it} \quad (1)$$

In regression model 1 *R* refers to the continuously compounded daily return on the stock market index for index *i* on day *t.* Index *i = {e,d}* refers to the aggregated emerging and developed indices in the global and continental panels. R_{it-1} and R_{it-2} are the lagged daily stock returns of the index, this term is included to account for first and second-order serial correlation (Hill, Griffiths & Lim, 2008). $D_t = \{D1_t, D2_t, D3_t, D4_t\}$, are dummies for Monday through Thursday effects, and H_t is a dummy that becomes 1 if the previous day was a non-weekend holidays. T_t is a dummy for the first five days of the taxation year, P_t is a dummy for the annual event period from June to July and J_{it} are two dummy variables that take the value one for the ten best and ten worst return days of the year. *Tt* is to control for the January effect (Dyl & Maberly, 1992), *Pt* is to control for seasonal effects and *Jit* are dummies to decrease the sensitivity to outliers. *EED* is the dummy variable of interest and refers to the *Event Effect Days*. These are days defined as a match day and the subsequent trading day. The same day is included to accommodate different time zones. To be able to compare the negative impact on stock prices in the developed and emerging indices, the EED variable becomes zero for the event effect days of the developed indices and one for the event effect days of less developed indices. The coefficient γ_8 captures the difference of the aggregate loss effect in both indices. Model 1 is used to estimate the effects in the global and continental panel separately. In the model only event effect day observations are used.

3.2.2 Differences from the methodology of Kaplanski and Levy (2010)

In the methodology of Kaplanski and Levy (2010), the impact of market sentiment on the New York Stock Exchange (NYSE) is investigated. Similarly, the authors use model 1. However, there is a major difference in the construction of the EED variable. In the original paper the EED variable becomes 1 for event effect days and zero for all other trading days. In my method only event effect days are used and all irrelevant non-match day observations are not taken into account.

When I would follow their methodology I would have to estimate four separate regressions, two for the indices in my global panel and two for the indices in my continental panel. Moreover, I would not be able to make a direct comparison between two indices. By combining my four indices into two panels I obtain multiple advantages.

First of all, it enables me to directly compare the impact of sentiment in emerging and developed markets. This is necessary in order to test my hypothesis. Second, I gain statistical advantages. The number of EED observations and the degrees of freedom increase. Besides, it only requires estimation of two regression models instead of four. This decreases the total number of parameters that need to be estimated and thus increases the degrees of freedom. In both cases, combining indices give more robust results.

3.2.3 Detecting heteroskedasticity and serial correlation

When building a multiple regression model using least squares estimators, assumptions of the Gauss-Markov theorem must be met in order to get the Best Linear Unbiased Estimators (BLUE). For the regression estimators to be BLUE, the theorem requires the residuals of the model to have an expected value of zero, an equal variance over time (homoscedastic) and to be uncorrelated (no serial correlation) (Verkbeek, 2008).

Model 1 is first regressed in STATA using a normal OLS regression with the `regress` function. After estimating the OLS regression the raw abnormal returns (or residuals) are obtained. Abnormal returns are the differences between the actual values and the predicted values, this is the part that cannot be explained by the model. One problem estimating this model with an OLS regression is that it assumes a constant volatility of the residuals. Scientific evidence in multiple studies showed that stock return data has a volatility that is varying over time (Bollerslev, Engle, & Nelson, 1994; French, Schwert, & Stambaugh, 1987). In statistical terms this is called heteroskedasticity. As a result, the standard errors of the residuals can be biased downwards in periods of high volatility. Consequently, the significance levels could be higher than the actually are. To overcome this misinterpretation I estimate regression 1 using a Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) model. The model was introduced by Engle (1982) and generalized by Bollerslev (1986). The conditioned volatility in GARCH improves the precision of the model and captures the stylized features of the real world volatility of stock returns (unpredictable observations with time varying volatility). The GARCH model is estimated with one lag of the regression model's squared residual (lagged ARCH term) and one lag of the variance (GARCH term), making it a GARCH (1, 1) model. The STATA command for this model is `regress arch(1) garch(1)`. After estimating regression 1 with GARCH, the index returns are normalized in way that the regression mean and standard deviation of the whole series are equal to those of the original series. The normalized residuals can now be obtained.

In figure 1 the raw residuals of all indices are shown on the left hand side. The variance is not constant over time. When the residuals are normalized, less weight is attached to high standardized errors and the regression coefficients of model 1 are more robust. By visual inspection of the normalized residuals on the right hand side of figure 1, it can be seen the variance of the normalized residuals has decreased.

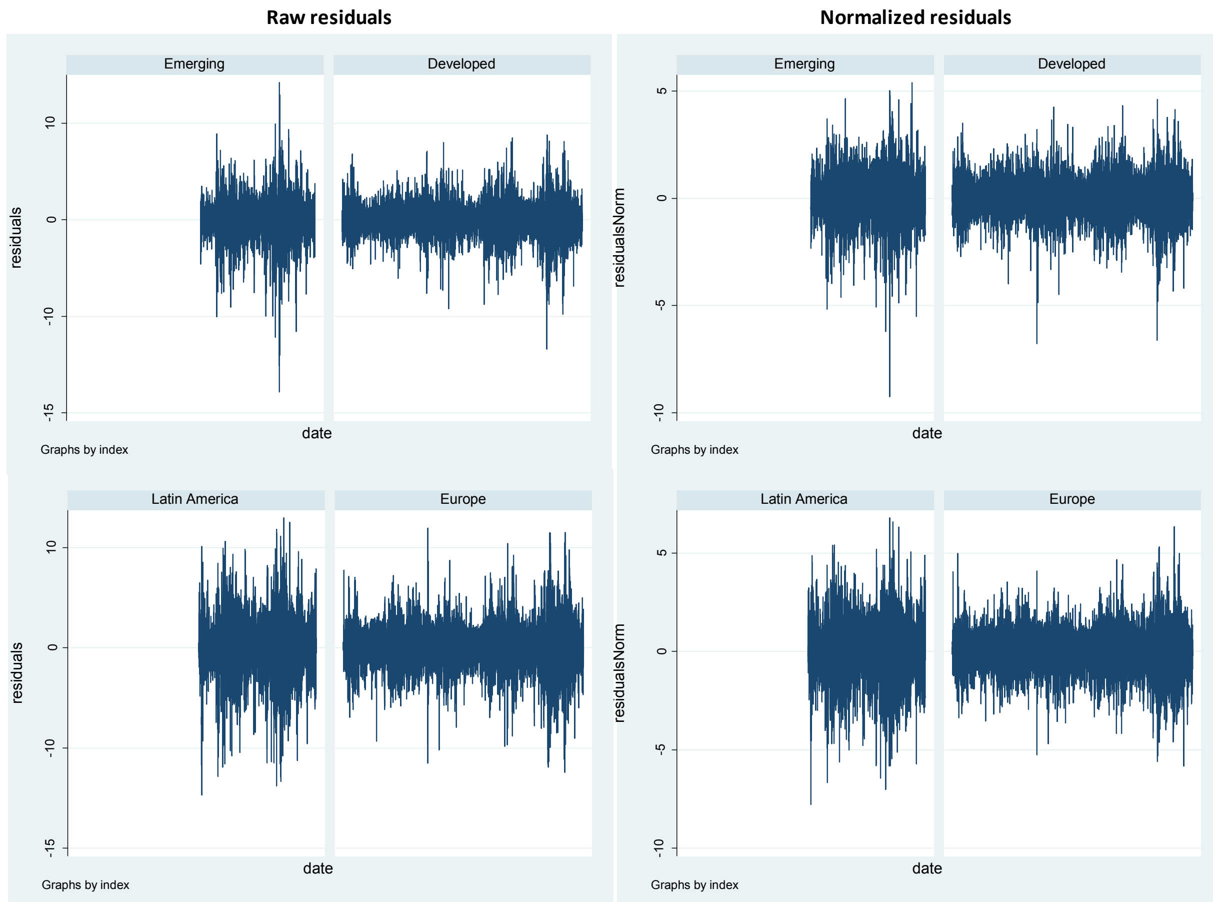

Figure 1. Residual plots of the raw and normalized residuals in the aggregate market method

Besides heteroskedasticity, I also test for serial correlation. Serial correlation also biases the standard errors and causes the results to be less efficient (Drukker, 2003). To test for serial correlation, I use Wooldridge's test developed by Jeffrey Wooldridge in 2002. The test relies on Wald test under the null hypothesis that there is no serial correlation (Wooldridge, 2010). Furthermore, Drukker (2003) provides evidence that the Wooldridge test has good size and power properties given the sample has a moderate size. In statistics size refers to the probability of falsely rejecting the null hypothesis and power refers to the probability that a test correctly rejects the null hypothesis. In STATA the `xtserial` command is used to test model 1 for serial correlation in both panels using the OLS regressions. With an F-statistic of 112.43 and a corresponding p-value of 0.06, the global panel has no serial correlation at a 5% confidence interval. The continental panel has an F-statistic of 33.17 and a p-value of 0.11. Thus we cannot reject the null hypothesis of no serial correlation in this panel either.

3.3 Results: The aggregate loss effect

Before estimating the aggregate market model, I first replicated the Kaplanski & Levy (2010) results. By being able to replicate the results I make sure that the basics of my methodology are safe and sound. The detailed description of the replication results can be found in appendix 2. Although the effects of the control variables were not similar, the effect of the variable of interest, EED, only differed 0.1% in both the OLS and GARCH models.

Performing the OLS and GARCH regressions with the aggregate market method has an effect on some of the control variables of the model. The independent variables for the non-weekend holiday (*Ht*), the first five days of taxation (*Tt*) and the 10 best and worst return days (*Jit*) are found to be too dependent among each other. That is, these are all dummy variables that can be written as a function of other dummy variables. Consequently, STATA drops out these variables. In statistical terms this is called multicollinearity (Farrar & Glauber, 1967). Statistically, this can be problematic in my regression model because multicollinearity can influence the beta of the EED coefficient. However, as long as the independent variables that are still in the regression model are not collinear with EED, the beta of my variable of interest is not affected.

Emeriging vs Developed

	Rt-1	Rt-2	NWH	Monday	Tuesday	Wednesday	Thursday	First 5 days	JuneJuly period	Ten-best	Ten-worst	EED
						Full model with control variables						
OLS model	0.0026	-0.0016	-	0	0.0009	-0.0010	0.0012	-	-	-	-	**-0.0003**
t-values	*(3.33)*	*(-1.78)*	*(omitted)*	*(-0.02)*	*(0.53)*	*(-0.51)*	*(0.78)*	*(omitted)*	*(omitted)*	*(omitted)*	*(omitted)*	***(-0.2)***
GARCH model	0.0020	-0.0008	-	0.0006	0.0017	-0.0010	0.0015	-		-	-	**-0.0010**
t-values	*(3.19)*	*(-1.21)*	*(omitted)*	*(0.32)*	*(0.96)*	*(-0.52)*	*(0.99)*	*(omitted)*	*(omitted)*	*(omitted)*	*(omitted)*	***(-0.76)***
						Model without control variables						
OLS model	-	-	-	-	-	-	-	-	-	-	-	**-0.0005**
t-values												***(-0.36)***
GARCH model	-	-	-	-	-	-	-	-	-	-	-	**-0.0013**
t-values												***(-0.96)***

Latin America vs Europe

	Rt-1	Rt-2	NWH	Monday	Tuesday	Wednesday	Thursday	First 5 days	JuneJuly period	Ten-best	Ten-worst	EED
						Full model with control variables						
OLS model	0.0013	-0.0003	-	0	0.0005	-0.0011	-0.0006	-	-	-	-	**-0.0008**
t-values	*(1.76)*	*(-0.44)*	*(omitted)*	*(0.17)*	*(0.22)*	*(-0.52)*	*(-0.3)*	*(omitted)*	*(omitted)*	*(omitted)*	*(omitted)*	***(-0.49)***
GARCH model	0.0013	-0.0003	-	0	0.0012	-0.0009	-0.0009	-	-	-	-	**-0.0009**
t-values	*(2.17)*	*(-0.48)*	*(omitted)*	*(0.35)*	*(0.52)*	*(-0.42)*	*(-0.44)*	*(omitted)*	*(omitted)*	*(omitted)*	*(omitted)*	***(-0.59)***
						Model without control variables						
OLS model	-	-	-	-	-	-	-	-	-	-	-	**-0.0007**
t-values												***(-0.41)***
GARCH model	-	-	-	-	-	-	-	-	-	-	-	**-0.0008**
t-values												***(-0.61)***

Table 1. Results table of the aggregate market method

I regressed EED on the control variables and very little correlation was found for the remaining independent variables. For the results please go to appendix 3.

The outcomes of the difference in aggregate effects of the two datasets are presented in table 1 above. All coefficients of EED of both datasets seem to show a more negative effect for the global emerging markets index and the regional Latin American index ranging from -0.3 to -1.3 basis points. None of these coefficients are significant, meaning we cannot make statistical inference from these results. The variables that were dropped out by STATA are denoted as *omitted.* The analysis also contains results excluding all control variables in order to increase the significance level of my variable of interest. The model without control variables does not significantly affect the significance of the variable of interest, EED. Furthermore, performing a GARCH regression does not improve the estimates enough to be able to make statistical implications. Concluding from these results I cannot reject the null hypothesis of the aggregate loss effect being stronger in less developed markets than in mature markets.

4 The local market model

In this section I describe the extension of the method by Edmans, Garcia and Norli (2007), which I labeled the "local market method". The local market method uses different proxies to measure the level of market development. In the method I use the following observable characteristics: the human development index, MSCI market classification, GDP per capita, volatility and liquidity. The construction and relevance of the development proxies are discussed in the first part of this section. Subsequently, these proxies are used in a dummy and continuous variable analysis to compare the loss effect[4] in different local stock markets. The method uses a panel with return indices from 53 countries and the panel regressions are estimated on GARCH adjusted returns using panel corrected standard errors (PCSE) in both analyses.

4.1 Data

4.1.1 Financial and soccer data

For the local market model, I decided to collect total return indices for all countries from only one data source. The data was downloaded from Datastream. Each country or regional return index has different starting dates, depending on the availability of volume data[5] of each index. In total I managed to gather financial data from 53 countries, 6 regional benchmark indices[6] and 1 global benchmark index. The *main panel* uses all country indices and the Global Equity World Index as benchmark. The regional indices together with all country indices are used to construct my *robustness panel*. In total there are 295.090 return days both the main panel and robustness panel. For a summary of my time series data please see appendix 1. Next to time series data, international soccer results from January 1973 through July 2014 were collected. I collected all historical match data applying the same procedure I used in the aggregate market method. The data includes World Cup matches, European Championship matches, Asia Cup matches and Copa America matches. The total number of matches that I collected were 1108, of which 520 were losses and 588[7] were wins. Since I evaluate the effect after lost matches, I only use 520 matches in my analysis. My panel data can be described as "long and wide" because I have observations of 53 countries in my sample over a time period of 1973 until 2014. The panel is unbalanced because not

[4] Recall: the negative impact on stock returns after a soccer match was lost
[5] The starting date of each index is the first day on which the volume traded reached 100
[6] Regional benchmarks: Europe, South-Europe, Americas, Latin-America, Asia, South-East Asia
[7] These matches are only used in order to replicate the results of Edmans, Garcia and Norli (2007) in appendix 6

all time periods of the countries are equal. The format of the FIFA tournaments is already discussed in section 3.1.2.

4.1.2 Market development proxies

1. Human Development Index

The Human Development Index was created to emphasize that people and their capabilities should be the ultimate criteria for evaluating a country's level of development[8]. It is an index, which ranks most countries taking into account key aspects of human development as well as economic growth. When computing the Human Development Index, data of life expectancy at birth, mean and average years of schooling and GNI per capita (purchasing power parity per capita) of a country are taken into account. Appendix 4 presents the human development rank of all countries in the dataset in 2013. The countries in my dataset are ranked between 0.45 and 0.95. The data was downloaded from the Human Development report 2014. In the report, there are also historical Human Development Index numbers of 1980, 1990, 2000, 2005, 2008, 2010, 2011 and 2012. These yearly historical index numbers were inserted in the dataset until a new number could replace the old. The variable is named "*HDI*".

2. MSCI Market Classification

A more abstract measure for the level of market development is the market classification by Morgan Stanley[9]. The countries are classified in three groups: frontier markets, emerging markets and developed markets. The data has been downloaded from the Morgan Stanley website. The classification is constructed based on three criteria: economic development, size and liquidity requirements and market accessibility. The market classifications of all countries in my panel and the framework used to assess the classification are presented in appendix 4. The disadvantage of this measure is that there are no relative weights of development across countries. It is a categorical variable. However, it is still possible to compare irrationality in different markets using the market classification as dummies. The variable is named "*market type*".

3. GDP per capita

GDP per capita is generally used as an indicator for economic development. The larger the average income per person is, the higher the level of development of a country. An increase in a country's GDP per capita often goes hand in hand with economic growth and prosperity (King & Levine, 1993). The data

[8] The data and information is gathered from the official website: http://hdr.undp.org/en/data
[9] The data and information is found on their official website: https://www.msci.com/market-classification

of the yearly rates of GDP per capita was obtained from the World Bank database[10]. Data was available for all countries except South Korea. Exclusion of South Korea's matches decreased the total number of observations from 520 to 492. The GDP per capita ranges from 700USD to 90.000USD for all observations of interest. To be able to use the data in a regression analysis without having magnitude problems for interpretation of the coefficient of the GDP per capita variable, the GDP per capita variable is divided by 10.000. This leaves a range from 0.07 to 9, a scale that is comparable to the other variables. The variable is named *"GDP"*.

4. Volatility

An important indicator for instability in an economy is the volatility of stock markets. The higher the degree of stock price deviations is, the higher the volatility and also the risk of the investment. It is generally known that emerging economies are often less stable and experience higher levels of volatility than more developed markets (Bekaert, & Harvey, 1997). For the volatility proxy, I calculated the annualized volatilities for all years and countries in my data. The following formula is used:

$$Annualized\ volatility = AV\ \sigma\ it * \sqrt{\#\ trading\ days\ it}$$

Where $AV\sigma\ it$ is the average daily volatility of country *i* at year *t* and $\sqrt{\#\ trading\ days\ it}$ are the number of trading days in the index of country *i* during the same year *t*. The second part of the formula is to account for small differences in the number of trading days across indices. The annualized volatility values range from 6.4 to 45.5. Once the ratio was calculated they are divided the values by 10 to make sure they are on the same scale as the other development proxies. The name of the variable is *"volatility"*.

5. Liquidity

In liquid markets, there is a lot of trading activity and trades are easily and quickly executed at the desired price. When there are many buyers and sellers active in the market, stock prices tend to be more stable. Therefore, the volatility in liquid markets is often lower. All in all, liquidity is an important attribute of the level of market development because it enhances the allocation of capital and increases the prospects of economic growth on the long term (Demirgüç-Kunt, & Levine, 1996). As a liquidity proxy, I use the turnover ratio of domestic shares traded relative to the market capitalization. The data of the yearly liquidity rates is downloaded from the World Bank database[11] and was available for all countries except South Korea. There were 22 observations with an extremely high liquidity ratio. These

[10] http://databank.worldbank.org/data/home.aspx
[11] http://databank.worldbank.org/data/home.aspx

observations are considered outliers biasing the proxy and were removed. The observations of interest decreased from 520 to 470. There were countries that had some years in which they did not report the liquidity level. In this case the old liquidity level was inserted until a new number could replace the old. The liquidity ratio ranges from 0.4 to 280. The variable has been divided by 100 to prevent a magnitude problem for the regression coefficients, leaving a range from 0.004 to 2.8. The variable is named *"liquidity"*.

4.1.3 Correlation matrix and internal consistency

To check the dependency among the development proxies, I estimated a correlation matrix. In table 2 you can see the matrix.

	hdi	**markettype**	**gdpcapita**	**volatility**	**liquidity**
hdi	1.00	-	-	-	-
markettype	0.69	1.00	-	-	-
gdpcapita	0.82	0.67	1.00	-	-
volatility	-0.43	-0.49	-0.43	1.00	-
liquidity	0.32	0.41	0.36	0.07	1.00

Table 2. Correlation matrix of the development proxies

From this correlation matrix it can be concluded that the correlation between GDP, HDI and market type is substantial. This is no surprise since GDP is generally known to be a good proxy for a country's level of development and HDI and market type also reflect market development. Earlier, I mentioned that higher liquidity is often present in mature markets. Therefore the positive correlation between liquidity, HDI, GDP and market type is also expected. Volatility is almost uncorrelated with liquidity, this is unexpected since liquid markets tend to be less volatile. The volatility is negatively correlated with HDI, GDP and market type. This is in line with the theory that emerging markets generally have higher volatility levels. This is further underlined by literature in section 1.3, where a negative relation was found GDP per capita and the level of price deviations (Lim & Brooks, 2010).

To find out the extent to which my proxies measure the same latent variable the internal consistency must be investigated. The most commonly used measure is Cronbach's alpha (Cronbach, 1951). Generally, an acceptable alpha ranges from 0.7 to 0.9. Given that my "construct" of market development/maturity is complex and multidimensional, it could be that some of my variables measure different dimensions of the latent construct. Therefore I believe a lower than 0.7 alpha is acceptable in my analysis. Cronbach's alpha is calculated using the `alpha` command in STATA. The alpha for my five development variables is 0.37, which is below the acceptable level.

Given the moderate correlation between liquidity and volatility, it could be that these variables decrease the internal consistency. Possibly, either liquidity or volatility is not related to the level of market development/maturity. A different reason for the questionable alpha could be that the level of market development has more observable aspects that should be taken into account when assessing this latent construct. When more relevant proxies are used, a larger part of the latent variable is explained. This should result in a higher alpha. Excluding liquidity from the estimation of Cronbach's alpha results in an alpha of 0.39. Exclusion of volatility from the Cronbach's alpha estimation results in an alpha of 0.63. With an alpha of 0.63 I believe the proxies are a reliable measure of market development.

4.2 The local market method

4.2.1 The basic model

I first estimate the following model for each country simultaneously, which is comparable to the method in section 3.2. Only the differences between this and my previous method are discussed.

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

In regression model 2 R_{it} refers to the continuously compounded daily return on the stock market of country i at year at year t. $D_t = \{D1_t, D2_t, D3_t, D4_t\}$, are dummies for Monday through Thursday effects. R_{mt} is the benchmark index, which refers to the continuously compounded daily return of Datastream's Global Equity Index: the World Market index. This variable is included to account for the correlation of integrated international stock markets across countries (Edmans, Garcia & Norli, 2007). Also a lagged and lead term are included, R_{mt-1} and R_{mt+1}, because some markets are leading the world market in time and some markets are lagging in time. $Q_t = \{Q1_t, Q2_t, Q3_t, Q4_t, Q5_t\}$ are dummies that become 1 if the previous 1 through 5 days were non-weekend holidays. In STATA the `regress` command is used to estimate this model.

To account for the heteroskedastic nature of stock returns model 2 is also regressed using GARCH(1,1). The index returns are normalized with a different procedure than in the aggregate market method. Here, the returns are normalized in a way that the mean of the returns are zero and the standard deviation is equal to one. Normalizing the mean and the standard deviation of all returns eliminates the heterogeneity in volatility across countries (Edmans, Garci, & Norli, 2007). The normalized returns are then used to obtain the normalized abnormal returns, the normalized residuals.

In order to compare irrationality in different markets, I first have to show that a negative impact on stock returns after lost soccer matches present in the main panel. To capture this effect the normalized residuals are used as the dependent variable in the following model.

$$\varepsilon_{it} = \beta_0 + \beta_1 L_{it} + U_{it} \tag{3}$$

In regression model 3, ε_{it} denote the normalized residuals for the index of country *i* at year *t* and β_0 is the constant factor. L_{it} is a loss dummy that takes the value 1 for the first trading day after a match was lost (loss day) and zero for the first trading day after a win. U_{it} is the error term. Consistent with the methodology of Edmans, Garcia and Norli (2007) and Hirshleifer and Shumway (2003), regression model 2 is estimated using panel corrected standard errors (PCSE). In STATA I use the command `xtpcse`. With PCSE, the error term U_{it} has a mean of zero and is uncorrelated over time. Moreover, it allows for heteroskedasticity and correlation across countries at the same time (Edmans, Garcia, & Norli, 2007).

The methodology used in the basic model is similar to the method of Edmans, Garcia and Norli (2007). In the methodology sections that follow (section 4.2.2 and section 4.2.3), I elaborate on the extensions of their method.

4.2.2 Measuring the effect with dummy variables

In order to investigate whether irrationality and thus the loss effect is more pronounced in less developed markets, I first use dummy variables. In this analysis only loss day observations[12] are considered. The advantage of using dummies is that the variable immediately gives the coefficient of interest, comparing one group to the other. On the other hand, I need to make a somewhat ad hoc split of the development proxies and I am not able to measure a possible linear relationship between the variables and the abnormal returns

To construct the dummies, I split each of my five development proxies in two groups. The dummies take the value zero for observations representing the characteristics of developed markets. These are the observations with a developed market characteristics, high human development index, high GDP per capita level, low volatility level and high liquidity level. The dummies take the value one for observations with the opposite characteristics, representing less developed markets. I tried to construct the groups in such a way that the two groups are divided in approximately two equal samples. The split of each variable is presented in the table 3 on the next page.

[12] All observations on days after soccer matches were lost

(HDI)	Groups	N
Baseline (0)	>0.75	340
Effect (1)	0.45 - 0.75	180
(Market type)		
Baseline (0)	Developed	227
Effect (1)	Emerging and frontier	293
(GDP)		
Baseline (0)	>20000	232
Effect (1)	0 - 20000	260
(Volatility)		
Baseline (0)	0 - 15	283
Effect (1)	>15	237
(Liquidity)		
Baseline (0)	>50	233
Effect (1)	0 - 50	237

Table 3. Dummy variables of the development proxies

To analyze the local market loss effect with dummies we use following model:

$$\varepsilon_{it} = \beta_0 + \beta_1 P_{it} + U_{it} \tag{4}$$

The model is comparable to regression model 3. ε_{it} , β_0 and U_{it} are exactly the same. In this model, P_{it} stands for the development dummy variables; HDI, market type, GDP, volatility and liquidity. An important difference with model 3 is that in model 4 only loss day observations are taken into account. Because the dummy takes value one for the group[13] that is expected to have more negative impact on the residuals, the coefficient β_1 is expected to be negative. All dummy variables are regressed separately using PCSE.

An important issue of my multiple-regression procedure is the problem of multiple testing or the multiplicity problem. Using different variable splits all accounting for the same latent variable to test for irrationality in the market, the probability of getting at least one significant result increases with every regression. Therefore, significance levels should be adjusted accordingly if the results are significant. Controlling for falsely rejected hypotheses, one can use methods such as the Bonferonni correction (Benjamini, & Hochberg, 1995). These correction methods are discussed in more detail once the results are presented.

[13] This group refers to the observations with emerging market characteristics.

4.2.3 Measuring the effect with continuous variables

Perhaps an even better method to test the relation between my development proxies and the loss effect is to investigate this relation with continuous variables. Using the proxies as continuous variables, we can investigate if there is a linear relation between the development proxies and the loss effect. Because *market type* is a categorical variable that does not reflect relatively weighted values, this variable is excluded from the continuous analysis. In this method all match day observations[14] are taken into account. The following model is estimated for all continuous development variables:

$$\varepsilon_{it} = \beta_0 + \beta_1 * P_{it} + \beta_2 * L * P_{it} + U_{it} \qquad (5)$$

Where ε_{it} denotes the normalized residuals, β_0 is the constant and $\beta_1 * P_{it}$ is the baseline effect of the development proxy and the abnormal returns. $\beta_2 * L * P_{it}$ refers to the interaction between a loss day and one of the development proxies. This interaction factor captures the added effect of the development proxy conditioned on loss days in relation to the abnormal returns compared to the baseline effect between P and ε. If the slope of β_2 is significant and positive (negative), the negative impact of loss days on stock returns is smaller (larger) when the value of development proxy P increases[15]. A quadratic function can be added to model 5 if there are signs of non-linearity in the model. Non-linearity is further investigated in the results section. As with the dummy variable analysis, model 5 estimated with a PCSE.

4.2.4 Detecting heteroskedasticity and serial correlation

For the local market method, I want to investigate heteroskedasticity and serial correlation as well. In figure 2 the residual plots of Greece and Turkey are shown. For the plots of all other countries please go to appendix 5. The residuals plots have the same interpretation as in section 4.1.3. By visual inspection of the normalized residuals on the right hand side of figure 2, it can be seen that the variance decreased but not vanished. This part of the heteroskedasticity further addressed by using PCSE estimation. Since my panel consists of various countries having observations over several time periods, it is not unlikely there is some serial correlation between the residuals within each country. The Wooldridge test is used again to test the residuals for serial correlation. The F-statistic of the test using raw residuals is 5.17 and the corresponding p-value is 0.027, suggesting there is serial correlation in the panel at a 5% confidence interval. When the test is estimated using the normalized residuals, the F-statistic is 1.1 with a p-value of 0.29. This means the serial correlation is corrected using normalized residuals. I estimate all regression models using PCSE to correct for serial correlation and heteroskedasticity.

[14] All observations on days after soccer matches were lost and won

[15] This is the case for all proxies except for volatility, here it is the other way around

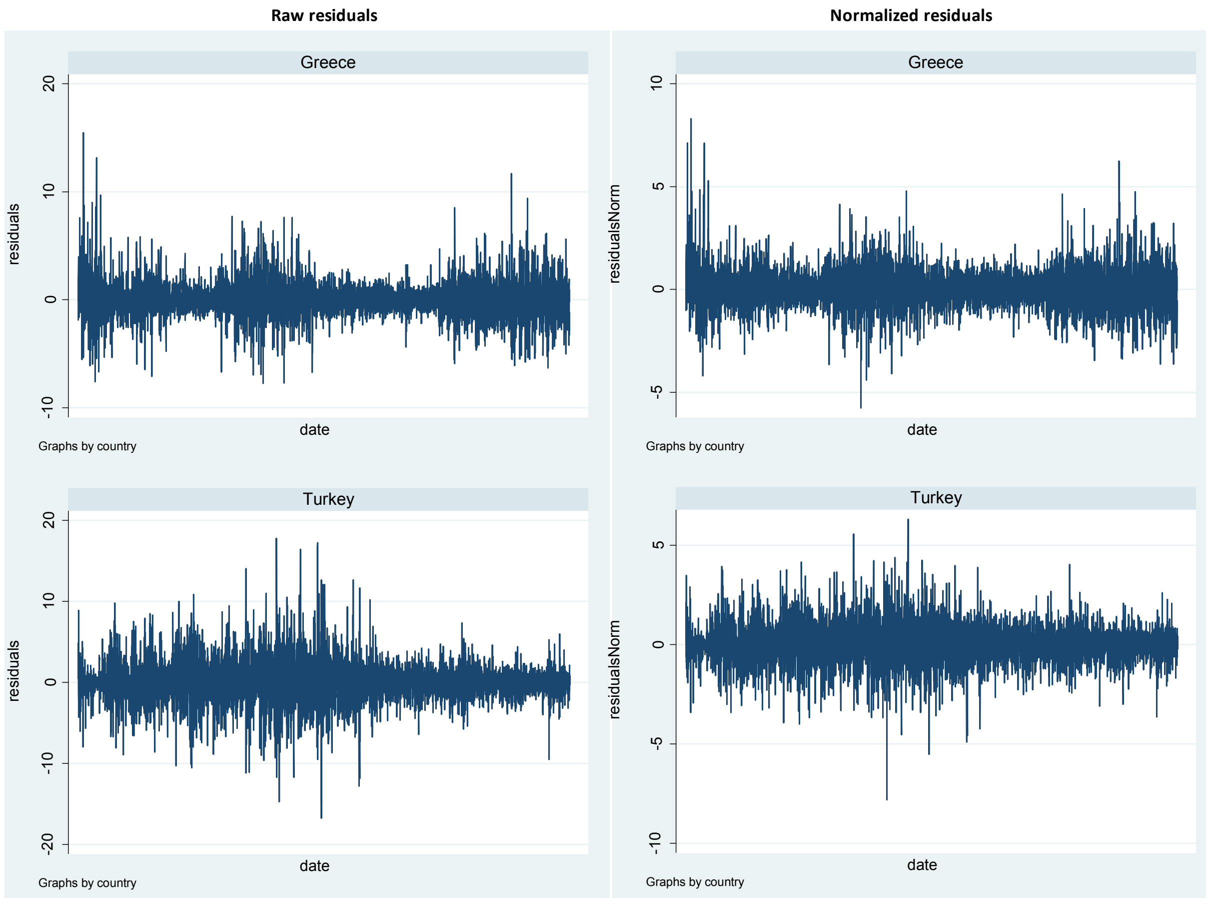

Figure 2. Residual plots of the raw and normalized residuals in the local market method

4.3 Results: The local market effect

4.3.1 The loss effect

Before I elaborate on the results of the dummy and continuous analysis, it is noteworthy to mention that I managed to replicate the method and results of Edmans, Garcia and Norli (2007). Restricting my dataset to match their data and by applying their methodology, the results of my analysis were comparable. For a full overview of the replicated results please go to appendix 6.

	N	β1* L	*z-value*
Main panel	520	-0.105	-2.42
Robustness check I	520	-0.097	-2.31
Robustness check II: Top 7 footbal nations	92	-0.229	-2.86
Robustness check II: Other nations	428	-0.079	-2.17

Table 4. Results of the loss effect and robustness checks

More interesting for my research is whether the loss effect in the main panel is still there. The results of this effect are presented in table 4 above an they were estimated using regression model 3. Despite the fact that the loss effect is still existent, the magnitude of the effect for the normalized residuals decreased from -0.16 (appendix 6) on the Edmans et al. data until 2007 to -0.11 on the extended data until 2014. The significance of the results also decreased. To test whether the loss effect is resistant to small methodological changes, I performed two robustness checks. As *robustness check I*, I analyzed the effect of loss games using the robustness panel with regional benchmark indices in order to capture regional shocks better[16]. For *robustness check II*, I performed the same robustness check used in the Edmans, Garcia and Norli (2007) paper. This robustness measure provides evidence for the fact that the loss effect is larger for observations of the top 7 soccer nations compared to the other nations in the dataset.

4.3.2 The local market effect using dummies

By using the dummy variables that were constructed earlier, we can now compare the loss effect in all groups. The results of the separate dummy regressions are presented in table 5.

[16] In the model for robustness check I, the lead term of model 2 is not included given there are little time differences in the same region.

	N	β1* P	*z-value*
HDI	182	0.060	0.84
Market type	293	-0.029	-0.44
GDP	260	0.003	0.04
Volatility	278	-0.085	-1.31
Liquidity	237	0.075	1.13

Table 5. Results table of the dummy analysis

In the table, N refers to the amount of observations of group 1, and β1*P refers to the dummy effect: the difference in impact of loss days on stock returns between the first group (1) and the baseline group (0). None of the betas of the dummies are significant. Although there are some negative coefficients, no statistical inference can be made from these insignificant results.

From these outcomes, the null hypothesis of hypothesis 2 cannot be rejected and therefore I cannot conclude that the local market loss effect is larger in less developed countries.

4.3.3 The local market effect using continuous variables

The results of the continuous variable analysis are presented in table 6.

	N	β1*P	β2 *PI*loss
HDI	520	-0.407	-0.141
		(-1.64)	*(-2.34)**
GDP	520	-0.030	-0.003
		(-1.91)	*(-0.2)*
Volatility	520	0.040	-0.084
		(0.9)	*(-2.88)**
Liqiudity	470	-0.032	-0.04
		(-0.54)	*(-0.67)*

Table 6. Results table of the continuous analysis

The HDI proxy seems to show a small effect significant at a five percent confidence level. On loss days the impact on stock returns decrease by 0.14*HDI, meaning the loss effect is increasing in the proxy. The effect is small since the most extreme HDI values in my data are 0.45 for the least developed country and 0.95 for the most developed country. This means that the negative impact of loss days on stock returns decreases by only 0.07[17] when comparing the most developed market to the least developed market. The effect is also contradicting my expectations that the negative impact after loss days on stock return would be smaller in more developed markets. A reason for this unexpected and trivial result could be that the number of observations in this regression is too small to capture the actual relation between HDI and the loss effect.

The volatility proxy also has an effect, which is significant at a 5% confidence level. Here, on loss days the impact on stock returns decreases by 0.08*volatility, meaning the loss effect is increasing in the volatility proxy. The normalized values of the volatility proxy in my data range from 0.64 to 4.55. This means that the negative impact of loss days on stock returns decreases with 0.31[18] when comparing the most volatile market to the least volatile market in my data. This effect is stronger and in line with my expectation. However, given the disturbing factor of volatility in the internal consistency on the level of market development (section 4.1.3), it is not sure that volatility explains part of the level of market development/maturity.

By looking a scatter plot of the dependent variable and the HDI and volatility proxies, I can observe if there is some form of non-linearity. When there is non-linearity in a plot, the marginal effect of the independent variable is not constant. Often some form of a U-shape can be detected. The plots in figure 3 do not show any form non-linearity. Therefore a quadratic function is not included.

[17] The difference between the two most extreme HDI values 0.95 and 0.45 is 0.5, the difference in effect is thus 0.5*-0.14 = -0.07

[18] The difference between the two most extreme volatility values 4.55 and 0.64 is 3.91, the difference in effect is thus 3.19*-0.08 = -0.31

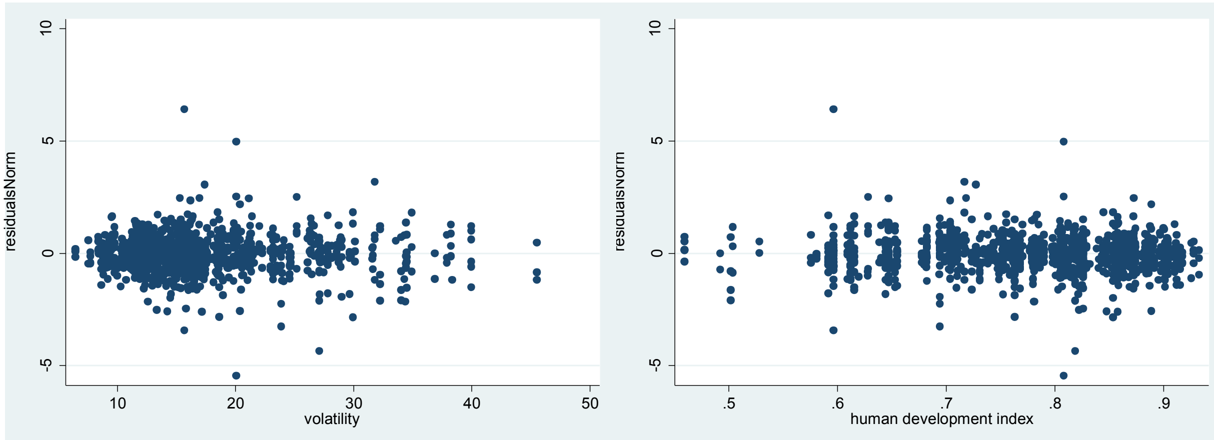

Figure 3. Scatter plots of normalized residuals with volatility and HDI

From the outcomes of the continuous variable analysis I cannot reject the null hypothesis of hypothesis 2. This means I cannot accept my second hypothesis and I cannot claim that the local market loss effect is stronger in less developed markets (countries) than in developed markets (countries).

4.3.4 Investigating the original loss effect of Edmans, Garcia and Norli

Since the results in both the dummy analysis and the continuous analysis were not strong enough to accept hypothesis 2, questions arise concerning the methodology and data used in the original paper by Edmans, Garcia and Norli (2007). To investigate the loss effect in my main panel, I used the same methodology as Edmans et al. (section 4.2.1). If this effect was not estimated properly and the loss effect is not present in my panel, lost soccer match days would be an unsuitable measure to capture irrationality in the market.

To further investigate this issue, I want to perform an outlier analysis on the negative impact of loss days on stock returns (loss effect) in my main panel. The outlier analysis is performed using two different methods. In the first method, *outlier analysis I,* I evaluate and exclude outlier years in my main panel. This analysis is presented in table 7. The outlier years that are excluded in this analysis are 2000 and 2002. 1989 is not excluded because the number of observations is only 2.

	N	β*L	*z-value*		N	β*L	*z-value*
1986	6	-0.328	-1.36	1999	16	-0.432	-1.94
1988	7	0.439	1.39	2000	35	-0.301	-2.41
1989	2	-0.248	-3.22	2001	10	0.005	0.04
1990	20	-0.083	-0.64	2002	34	-0.390	-2.42
1991	6	0.231	1.26	2004	50	0.064	0.84
1992	9	-0.084	-0.71	2006	25	-0.011	-0.11
1993	8	0.302	1.1	2007	31	-0.072	-0.86
1994	27	-0.132	-0.66	2008	28	-0.196	-1.34
1995	17	-0.103	-0.57	2010	29	-0.061	-0.68
1996	24	-0.154	-1.13	2011	27	0.008	0.09
1997	15	0.094	0.52	2012	26	-0.144	-1.48
1998	31	-0.122	-0.67	2014	37	-0.124	-1.4

Table 7. Outlier years table

In *outlier analysis II*, I use the Cooks's distance estimate to exclude outliers. Both outlier analyses are thoroughly explained in appendix 7. In table 8 all years are regressed with the Cook's distance estimate. Using Cook's distance, only year 2002 remains significant. The results of the outlier analyses I and II on the loss effect in the main panel are presented in table 9.

	N	β*L	*z-value*		N	β*L	*z-value*
1986	6	-0.350	-1.17	1999	16	-0.217	-1.19
1988	7	0.387	1.4	2000	35	-0.332	-2.69
1989	2	-0.250	-0.48	2001	10	-0.003	-0.01
1990	20	-0.086	-0.53	2002	34	-0.198	-1.58
1991	6	0.124	0.42	2004	50	0.006	0.06
1992	9	-0.094	-0.39	2006	25	-0.027	-0.18
1993	8	0.322	1.24	2007	31	-0.087	-0.66
1994	27	-0.018	-0.13	2008	28	-0.168	-1.21
1995	17	-0.114	-0.64	2010	29	-0.075	-0.55
1996	24	-0.081	-0.54	2011	27	-0.001	-0.01
1997	15	0.095	0.5	2012	26	-0.086	-0.6
1998	31	-0.006	-0.04	2014	37	-0.122	-1.01

Table 8. Outlier years table with Cook's distance estimation

	N	β*L	z-value
Main panel loss effect	520	-0.105	-2.42
Outlier analysis I	451	-0.069	-1.88
Outlier analysis II	520	-0.071	-1.81

Table 9. Results table of outlier analyses I and II for the overall loss effect

The outcome of this outlier analysis casts doubt about the irrational behavior of investors after loss-days found in the previous literature and in my local market method. The results of both outlier analyses clearly provide evidence that the loss effect becomes smaller and insignificant[19]. The fact the loss effect decreased or even disappeared, is supported by several papers discussed in the literature (Ashton, Gerrard & Hudson 2011; Kaplanski and Levy, 2014).

[19] The results of both outlier analyses are only significant at a 10% confidence interval.

5 Discussion

The limited number of significant findings in both the aggregate market method and the local method are a good reason to discuss the results. Evaluating the methodology and findings of this research paper enables me to propose clear recommendations for further research.

In both approaches, the aggregated market method and the local market method, that were used to investigate the main research question, different models were constructed in order to explain abnormal returns. When asset-pricing models are used to test for market inefficiency, the models can always be subject to the joint hypothesis problem. This problem implies that any test for market inefficiency is a joint test for mispricings and the validity of the model. According to Fama (1991), this problem makes precise inference about the level of market efficiency impossible and it leaves uncertain results. However, he also mentions that these uncertainties are unavoidable if one wants to add content to the existing strand of literature.

A limitation of this and previous research is the small number of observations. A small sample size decreases the power of the estimation models. Consequently, the chance of finding a relation in the investigated data decreases. I wanted to increase the number of observations by adding more international sport games into the main panel. However, constructing the datasets using only a single sport was already so time consuming that I had to restrict myself to soccer matches.

Since no significant negative impact on stock returns was found for the aggregate market method and the negative impact on stocks was marginal for the local market method, it is questionable whether emotions induced by soccer cause irrational trading behavior among investors. In the outlier analysis performed in section 4.3.4, this cast of doubt is supported. When soccer emotions do not affect trading behavior, it is impossible to compare irrationality in emerging and developed markets with the methodology I applied.

The negative results of the aggregate market method can also be subject to the type of data that is used. The method uses Datastream's Global Equity Indices that are constructed by aggregating market indices with the same characteristics or from the same geographical region. Although the Global Equity Indices provide an independent standard for equity research, it is not possible to trade actively in these indices. Given there are no direct trades on these indices, it could be hard to capture irrational trading behavior from all indices that are aggregated in these Global Equity Indices.

For the local market method, the selection of the development proxies can be a point of discussion. The fact that the volatility proxy decreased the internal consistency of the proxies to a lower level could mean that volatility should not be taken into account in future research. However, exploring different approaches to construct volatility can also resolve this problem. Without the volatility proxy, the internal consistency of measuring the level of market development/maturity was at an acceptable level. Given the multi-dimensional complexity of the latent construct of market development/maturity, I am convinced that my proxies are suitable for measuring this construct.

Proposals for future research

Future research can extend the aggregate market method by using different sport events and different local markets to reflect developing and developed markets. However, it seems to be complex to capture irrationality across markets with this method.

In my opinion, the local market method is more suitable for an extended research. The proxies for market development were solid and can be used to investigate various topics. Optimizing the amount and relevance of the development proxies can be an addition to the local market method. When the development proxies are optimized to best reflect the level of market development/maturity, the new proxies can be combined in one latent index of market development/maturity. Besides the construction of one latent index for market development, a factor analysis can be an interesting improvement of the methodology used in this paper.

The most straightforward proposal for future research using the local market method would be to find different events to capture market sentiment and irrationality in the market. Besides a good measure to capture irrationality, there should be enough observations to strengthen the power of the estimation models. I think it is challenging to find a different sentiment proxy that allows for a cross-country comparison and a large number of observations.

6 Conclusion

The traditional finance paradigm that investors are rational and markets are efficient is long gone. In the behavioral finance literature, sudden changes in investor mood caused by international soccer matches proved to have an impact on stock prices. This paper investigated whether irrational behavior as consequence of emotion was more pronounced in developing markets than in developed markets. In the paper, international soccer match outcomes were used as events that are likely to influence investor sentiment.

From the results of the two different approaches investigating this topic we cannot conclude that irrationality among investors is more pronounced in developing markets compared to developed markets. In fact no relation was found at all. In the first approach, the aggregate market method, no significant difference in the impact of soccer matches on stock prices was found between aggregated emerging market indices and aggregated developed market indices. As a result, the null-hypothesis was not rejected. The second method, the local market method, found no significant results for either of the proxies for market development/maturity when they were used in a dummy analysis. Using the development proxies as continuous variables, the method found a small negative relation of -14 basis points between irrationality on loss days and the human development index. This result contradicts the expectations that the negative impact on stock returns would be weaker in more developed markets. A negative relation of -8 basis points was found between the volatility proxy and irrational trading behavior. This relation is in line with the expectation that more volatile markets are more irrational. Given the found effects were contracting each other and there was no significant effect for the remaining proxies for market development/maturity, it cannot be concluded that irrationality in emerging markets is stronger compared to developed markets. The null-hypothesis for hypothesis 2 was not rejected either.

While this study was unable to find significant evidence to accept the hypotheses, there are renovating aspects in the methodology that can be used in further studies. Given that many studies found some connection between irrationality and aspects of market development, there are still enough reasons to believe a relation between these concepts could be present. In the local market method, the continuous variable analysis with the development proxies can be enhance in order to get more insight in this topic. That is, the next step in investigating this topic is to improve the power of the estimation models in such a way that relation between irrationality and the level of market development can be revealed.

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Appendices

Appendix 1. Time series data

This appendix contains all country (including corresponding numbers), global and regional indices that are both methods. For England, Wales and Scotland the same UK has been used. There were no separate indices available. All indices are total return indices on a daily base, downloaded from Datastream.

Country	Start historical data	Ticker	Country	Start historical data	Ticker
Argentina (1)	3/8/1993	TOTMKAR	Spain (32)	7/2/1990	TOTMKES
Australia (2)	5/1/1984	TOTMKAU	South Africa (33)	4/1/1990	TOTMKSA
Austria (3)	5/8/1986	TOTMKOE	Slovenia (34)	6/1/1999	TOTMKSJ
Belgium (4)	6/1/1986	TOTMKBG	Sweden (35)	7/1/1982	TOTMKSD
Brazil (5)	5/1/1995	TOTMKBR	Switzerland (36)	4/1/1990	TOTMKSW
Canada (6)	4/1/1974	TOTMKCN	Turkey (37)	6/1/1988	TOTMKTK
Chile (7)	5/7/1989	TOTMKCL	United States (38)	19/01/1973	TOTMKUS
China (8)	5/5/1994	TOTMKCA	Estonia (39)	5/6/1997	TOTMKEO
Colombia (9)	12/3/1992	TOTMKCB	Bulgaria (40)	2/10/2000	TOTMKBL
Croatia (10)	5/10/2005	TOTMKCT	Israel (41)	29/01/1993	TOTMKIS
Czech Republic (11)	6/1/1995	TOTMKCZ	Venezuela (42)	2/1/1990	TOTMKVE
Denmark (12)	9/10/1991	TOTMKDK	Peru (43)	3/1/1994	TOTMKPE
England (13)	29/10/1986	TOTMKUK	Jordan (44)	30/06/2006	TOTMKJO
France (14)	3/6/1988	TOTMKFR	United Arab Emirates (45)	31/12/2003	TOTMKAE
Germany (15)	15/06/1988	TOTMKBD	Bahrain (46)	31/12/2003	TOTMKBA
Greece(16)	3/1/1990	TOTMKGR	Kuwait (47)	31/12/2003	TOTMKKW
Ireland (17)	3/11/2000	TOTMKIR	Oman (48)	3/10/2005	TOTMKOM
Italy (18)	3/7/1986	TOTMKIT	India (49)	2/1/1995	TOTMKIN
Japan (19)	5/12/1990	TOTMKJP	Indonesia (50)	2/4/1990	TOTMKID
Mexico (20)	12/5/1989	TOTMKMX	Malaysia (51)	2/1/1986	TOTMKMY
Morocco (21)	5/4/1994	TOTMKMC	Wales (52)	27/10/1986	TOTMKUK
Netherlands (22)	5/2/1986	TOTMKNL	Qatar (53)	31/12/2003	TOTMKQA
New Zealand (23)	5/1/1990	TOTMKNZ	World index	1/1/1973	TOTMKWD
Nigeria (24)	10/9/2009	TOTMKNG	Americas index	2/1/1973	TOTMKAM
Norway (25)	5/1/1983	TOTMKNW	Europe index	7/1/1982	TOTMKER
Poland (26)	4/1/1995	TOTMKPO	S-Europe index	1/7/1986	TOTMKSS
Portugal (27)	3/1/1992	TOTMKPT	Asia index	4/7/1994	TOTMKAS
Romania (28)	6/5/1997	TOTMKRM	SE-Asia index	3/1/1983	TOTMKSE
Russia (29)	29/01/1998	TOTMKRS	Developed index	1/1/1973	TOTMKDV
Scotland (30)	29/10/1986	TOTMKUK	Emerging index	2/1/1995	TOTMKEM
South Korea (31)	11/9/1987	TOTMKKO	Latin america	4/7/1994	TOTMKLM

Appendix 2. Replication results of Kaplanksi & Levy (2010)

In panel A below you can observe the replication results of the method by Kaplanksi & Levy (2010). Kaplanki and Levy (2010) used regression model 1 to estimate the impact of market sentiment on the US stock market. The EED variable is constructed differently, it becomes 1 for all event effect days and zero for all non-match days. There are also some differences in my replication data compared to the original data. The original data has 243 EED observations starting from 1950, my data has 153 EED observations starting from 1973. Also, the US index used in the original method was an NYSE index from the CRSP database, my return index is the total US Market index downloaded from Datastream. Panel A represents the original and replication results using an OLS model and a GARCH model. The first line represent the regression coefficient of the independent variable and de second line denote the t-values. As you can see the variable of interest, EED, is just off with 0.0001 (0.1%) in both regression models. The outcome is significant, although a bit less significant than the original outcome. On the other hand the control variables were not comparable and in most cases insignificant. In panel B, I dropped the insignificant control variables to raise the significance of the EED variable. As you can see, this had almost no effect to the significance level. The regression coefficient of the OLS regression and GARCH increased and decreased with 0.0001 respectively. Kaplanski and Levy (2010) also compared the annualized EED return to the full year return. In all World Cup years that are present in in my dataset, the original results found that the annualized EED return was lower than the full year return. For my replication dataset this has also been calculated in panel C. Except for 1998, in all years the annualized EED return was smaller than the full year return. The probability of this happening is calculated with the following binomial statistic: $P = \sum_{x=8}^{9} \binom{9}{x} (0.5)^{x}\ (0.5)^{9-x}$. The null hypothesis that the annualized return during the Word Cup period is lower than the yearly return in all these years is rejected at 5% confidence interval with a p-value of 0.02. All in all, as I am only interested in the effect of World Cup match days (EED) on stock returns. Therefore I can conclude the results have been replicated.

Panel A: Replication of Kaplanski and Levy (2010)

(Variable)	Rt-1	Rt-2	NWH	Monday	Tuesday	Wednesday	Thursday	First 5 days	JuneJuly period	Ten-best	Ten-worst	**EED**
						Full model with control variables						
Original results	0.2288	-0.0256	0.0014	-0.0024	-0.0009	-0.0002	-0.0008	0.0029	-0.0001	-0.0587	0.0509	**-0.0016**
OLS	*28.89*	*-3.22*	*-2.92*	*-13.73*	*-5.17*	*-1.35*	*-4.47*	*5.27*	*-0.84*	*-27.42*	*23.72*	***-3.54***
Replication results	0.0593	-0.0317	0.0004	0	0.0000	0.0002	-0.0002	0	0	0.0629	-0.1002	**-0.0017**
OLS	*3.25*	*-2.23*	*0.54*	*-1.25*	*-0.07*	*0.69*	*-0.54*	*-0.04*	*-0.23*	*10.09*	*-4.07*	***-2.17***
Original results	-	-	0.0019	-0.0027	-0.0016	-0.0005	-0.0007	0.0043	-0.0001	-	-	**-0.0020**
GARCH			*3.67*	*-14.42*	*-8.5*	*-2.57*	*-3.98*	*7.47*	*-0.83*			***-4.09***
Replication results	-	-	0.0005	-0.0005	0	0.005	0	0.0007	0.0001	-	-	**-0.0019**
GARCH			*0.65*	*-1.33*	*0.04*	*1.43*	*-0.08*	*0.53*	*0.47*			***-2.29***

Panel B: Replication without control variables

(Variable)	Rt-1	Rt-2	NWH	Monday	Tuesday	Wednesday	Thursday	First 5 days	JuneJuly period	Ten-best	Ten-worst	EED
						Model without control variables						
Replication results	0.0593	-0.0319	-	-	-	-	-	-	-	0.0631	-0.1005	**-0.0018**
OLS	*3.25*	*-2.25*								*10.19*	*-2.34*	***-2.34***
Replication results	-	-	-	-	-	-	-	-	-	-	-	**-0.0018**
GARCH												***-2.28***

Panel C: Annualized EED returns compared to full year returns

	Annualized EED return	Yearly return	EED<Yearly return
1986	-2.35	17.67	yes
1982	1.84	25.77	yes
1978	7.01	7.61	yes
1974	-90.09	-30.17	yes
1990	-23.96	-0.19	yes

	Annualized EED return	Yearly return	EED<Yearly return
1994	-36.53	1.58	yes
1998	74.98	28.25	no
2002	-68.86	-21.10	yes
2006	-14.15	15.18	yes

Appendix 3. Testing for collinearity

To test the aggregate market method for collinearity, I regressed the variable of interest on all other independent variables for both datasets. You see below that all weekday variables were not omitted (0) because they have very little dependence on our variable of interest. These results explain that the EED variable is not be affected by the collinearity. The variable descriptions can be found in section 4.1.2.

Panel A: dataset 1, comparing the global emerging and global developed markets

Dependent variable	EED	Coef.	t
Independent variable	R-1	-0.0205	-0.61
Independent variable	R-2	-0.0040	-0.11
Independent variable	H	0	
Independent variable	D1	-0.0438	-0.5
Independent variable	D2	0.0041	0.04
Independent variable	D3	-0.0116	-0.13
Independent variable	D4	-0.0439	-0.49
Independent variable	T	0	
Independent variable	P	0	
Independent variable	J1	0	
Independent variable	J2	0	

Panel B: dataset 2, comparing the regional European and the regional Latin American markets

Dependent variable	EED	Coef.	t
Independent variable	R-1	-0.0086	-0.34
Independent variable	R-2	0.0056	0.22
Independent variable	H	0	
Independent variable	D1	-0.0327	-0.38
Independent variable	D2	-0.0061	-0.07
Independent variable	D3	-0.0119	-0.13
Independent variable	D4	-0.0427	-0.47
Independent variable	T	0	
Independent variable	P	0	
Independent variable	J1	0	
Independent variable	J2	0	

Appendix 4. Development proxies

In panel A below you see the 2013 Human Development Index rank and rank change from 2008 until 2013. In the dataset I inserted the changing HDI ranks over the years 2008 until 2013. For simplicity reasons, the historical HDI values are not presented in this table. In panel B, you can observe all MSCI market classification of the countries in my sample. The figure underneath are the criteria for the three different market classification of MSCI that were used to evaluate each markets. As mentioned in the main text, the data is gathered from the official MSCI website.

Panel A: Human development index

HDI rank	Country	2013	rank change 2008-2013	HDI rank	Country	2013	rank change 2008-2013
1	Norway	0.944	0	33	Estonia	0.84	0
2	Australia	0.933	0	35	Poland	0.834	3
3	Switzerland	0.917	1	40	United Arab E	0.827	-5
4	Netherlands	0.915	3	41	Chile	0.822	3
5	United States	0.914	-2	41	Portugal	0.822	3
6	Germany	0.911	-1	44	Bahrain	0.815	-2
7	New Zealand	0.91	1	46	Kuwait	0.814	1
8	Canada	0.902	1	47	Croatia	0.812	-1
10	Denmark	0.9	-1	49	Argentina	0.808	4
12	Sweden	0.898	-1	54	Romania	0.785	-3
14	England (UK)	0.892	-2	56	Oman	0.783	6
14	Wales	0.892	-2	57	Russia	0.778	0
14	Scotland	0.892	-2	58	Bulgaria	0.777	0
15	South Korea	0.891	5	62	Malaysia	0.773	1
17	Japan	0.89	-2	67	Venezuela	0.764	-2
19	Israel	0.888	-1	69	Turkey	0.759	16
20	France	0.884	0	71	Mexico	0.756	2
21	Austria	0.881	3	77	Jordan	0.745	-8
21	Belgium	0.881	1	79	Brazil	0.744	-4
21	Luxembourg	0.881	-6	82	Peru	0.737	8
25	Slovenia	0.874	-2	91	China	0.719	10
26	Italy	0.872	-2	98	Colombia	0.711	-2
27	Spain	0.869	1	108	Indonesia	0.684	4
28	Czech Republ	0.861	1	118	South Africa	0.658	2
29	Greece	0.853	-2	129	Morocco	0.617	3
31	Qatar	0.851	-1	135	India	0.586	1
				152	Nigeria	0.504	1

Panel B: Market Classifications and criteria

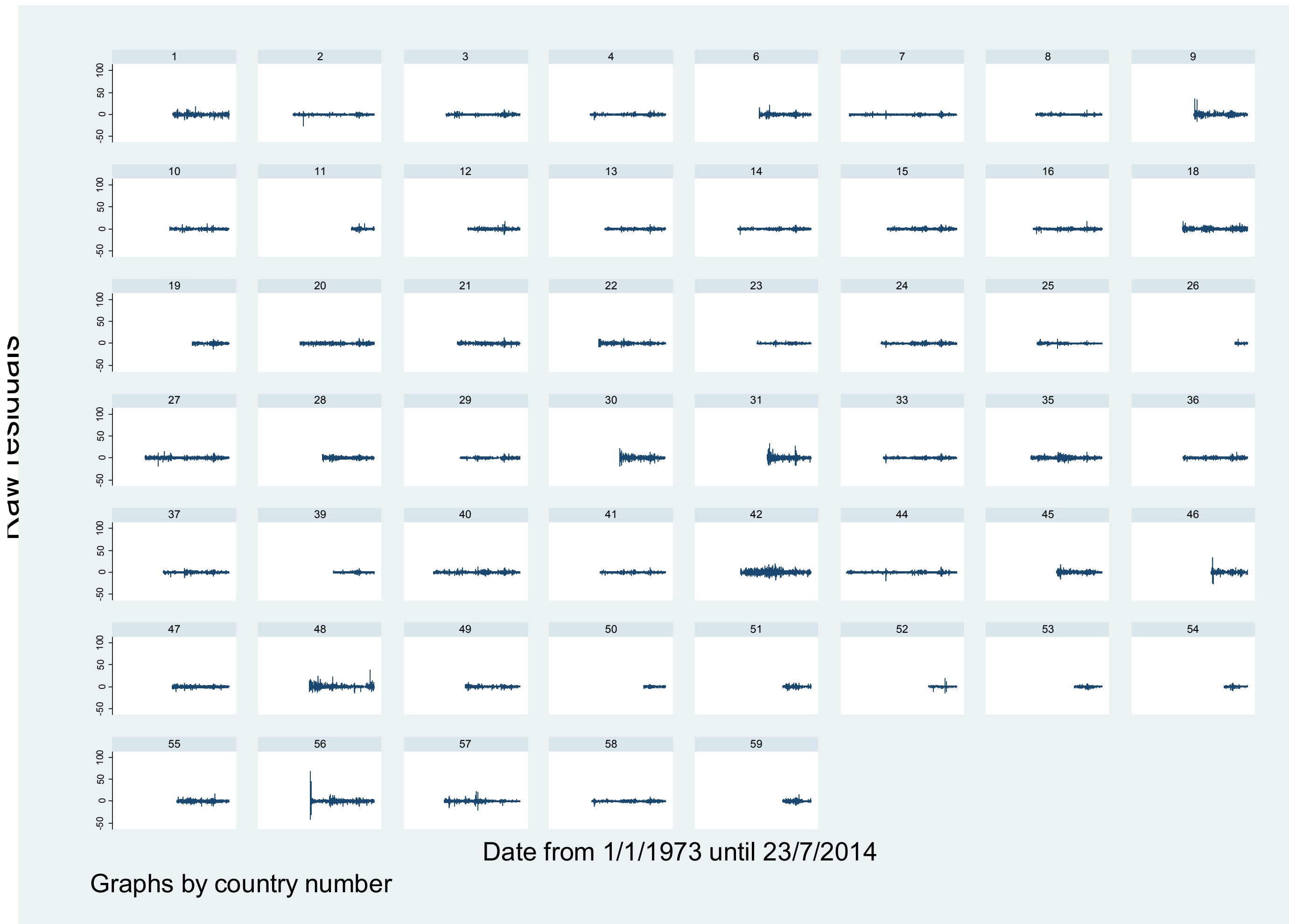
Country	Market classification	Country	Market classification
Argentina	MSCI Frontier markets	Romania	MSCI Frontier markets
Australia	MSCI Developed markets	Russia	MSCI Emerging markets
Austria	MSCI Developed markets	Scotland (UK)	MSCI Developed markets
Belgium	MSCI Developed markets	south korea	MSCI Emerging markets
Brazil	MSCI Emerging markets	spain	MSCI Developed markets
Canada	MSCI Developed markets	South africa	MSCI Emerging markets
Chile	MSCI Emerging markets	Slovenia	MSCI Frontier markets
China	MSCI Emerging markets	Sweden	MSCI Developed markets
Colombia	MSCI Emerging markets	Switzerland	MSCI Developed markets
Croatia	MSCI Frontier markets	Turkey	MSCI Emerging markets
Czech Republic	MSCI Emerging markets	United States	MSCI Developed markets
Denmark	MSCI Developed markets	Estonia	MSCI Frontier markets
England (UK)	MSCI Developed markets	Bulgaria	MSCI Frontier markets
France	MSCI Developed markets	Israel	MSCI Developed markets
Germany	MSCI Developed markets	Venezuela	MSCI Emerging markets
Greece	MSCI Emerging markets	Peru	MSCI Emerging markets
Ireland	MSCI Developed markets	Jordan	MSCI Frontier markets
Italy	MSCI Developed markets	United Arab Emirates	MSCI Emerging markets
Japan	MSCI Developed markets	Bahrain	MSCI Frontier markets
Mexico	MSCI Emerging markets	Kuwait	MSCI Frontier markets
Morocco	MSCI Frontier markets	Oman	MSCI Frontier markets
Netherlands	MSCI Developed markets	India	MSCI Emerging markets
New Zealand	MSCI Developed markets	Indonesia	MSCI Emerging markets
Nigeria	MSCI Frontier markets	Malaysia	MSCI Emerging markets
Norway	MSCI Developed markets	Wales (UK)	MSCI Developed markets
Poland	MSCI Emerging markets	Qatar	MSCI Emerging markets
Portugal	MSCI Developed markets		

	Frontier	Emerging	Developed
Criteria			
A. Economic Development	No requirement	No requirement	Country GNI per capita 25% above the World bank threshold for 3 consecutive years
B. Size and Liquidity Requirements			
B.1 Number of companies meeting following index criteria	2	3	5
Company size (full market cap)	USD 670 MM	USD 1340 MM	USD 2679 MM
Security size (float market cap)	USD 52 MM	USD 670 MM	USD 1340 MM
Security liquidity	2.5% ATVR	15% ATVR	20% ATVR
C Market Accessiblity Criteria			
C.1 Openness to foreign ownership	At least some	Significant	Very high
C.2 Ease of capital inflows/ outflows	At least partial	Significant	Very high
C.3 Efficiency of operational framework	Modest	Good and tested	Very high
C.4 Stability of the institutional framework	Modest	Modest	Very high

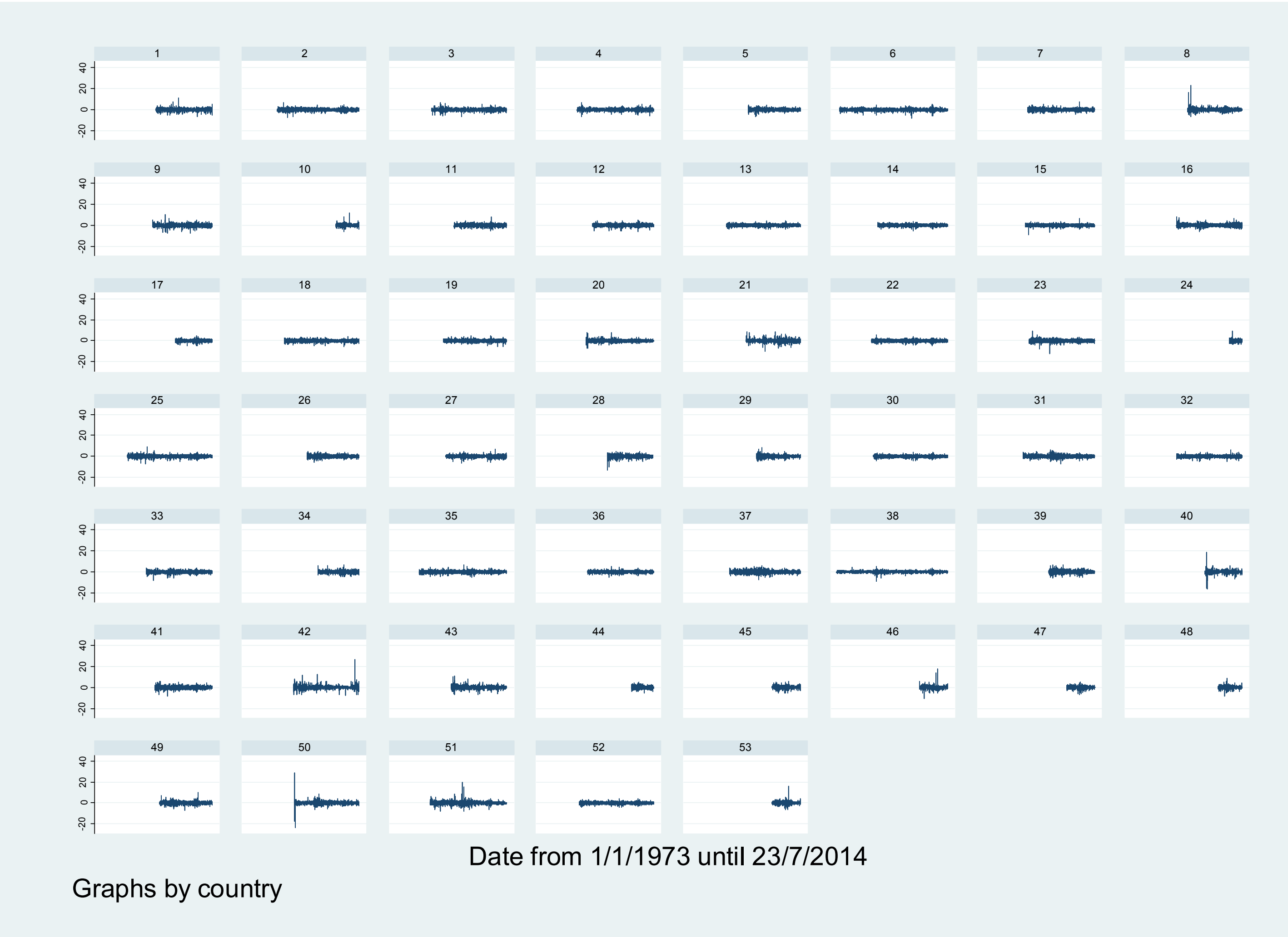
Appendix 5. Residual plots of all country indices

The panel A represents the raw residual plot for all countries in the main local market dataset. The corresponding country number can be found in appendix 1. Panel B shows the normalized residual plots.

Panel A: Residual plots using raw residuals



Panel B: Residual plots using normalized residuals



Appendix 6. Replication results of Edmans, Garcia & Norli (2007)

In the tables below you can observe the replication of the original method by Edmans, Garci & Norli (2007). The replication dataset contains 34 of the 39 countries in the original method. Furthermore, the panel has observations from 1973 until 2004. This is the same time span the original EGN method has, however the starting dates of some countries indices were different. Another difference is that I didn't include close qualification matches, this decreased the number of observation in my dataset. Like in the original method, the dataset contains soccer matches from the World Cup, the European Championship, the Asia Cup and the Copa America. In panel A you can observe the replicated results and in panel B the original results. You can observe that the coefficients of the loss effect are comparable, especially with the results for the normalized residuals. The effect after winning a match not really comparable. This is not strange given the dataset is slightly different and results were insignificant in the original method. Moreover, in this thesis we are only interested in the loss effect.

Panel A: Replication of Edmans, Garcia and Norli (2007)

		Wins			Losses	
Raw residuals	N	β W	*z-value*	N	β L	*z-value*
All games	330	0.068	1.24	269	-0.272	-4.38
Elimination	117	-0.045	-0.5	104	-0.324	-3.38
WC	47	0.066	0.47	42	-0.192	-1.38
Con	70	-0.12	-1.03	62	-0.413	-3.17
Group	213	0.13	1.9	165	-0.239	-2.95
WC	73	0.046	0.41	52	-0.48	-3.22
Con	140	0.174	2.02	113	-0.128	-1.33
Normalized residuals						
All games	330	0.036	0.8	269	-0.163	-3.43
Elimination	117	-0.047	-0.64	104	-0.155	-2.01
Group	213	0.081	1.44	165	-0.168	-2.81

Panel B: Original results

	Wins			Losses		
Raw residuals						
	N	β W	*z-value*	N	β L	*z-value*
All games	638	0.016	0.27	524	-0.212	-3.27
Elimination	177	0.046	0.43	138	-0.384	-3.24
WC	76	0.09	0.53	56	-0.494	-2.71
Con	101	0.052	0.09	82	-0.309	-1.99
Group	243	0.052	0.53	198	-0.168	-1.47
WC	115	0.007	0.05	81	-0.38	-2.23
Con	128	0.092	0.67	117	-0.022	-0.14
Normalized residuals						
All games	420	-0.019	-0.47	336	-0.157	-3.68
Elimination	177	0.026	0.35	138	-0.182	-2.17
Group	243	-0.034	-0.52	198	-0.179	-2.57

Appendix 7. Outlier analyses

To start with, I evaluate the possible outlier years. The outlier years correspond to soccer tournaments on which the negative impact on stock returns were abnormally high. Using the same methodology that was applied to measure the loss effect, I create dummies for each year in my sample. The outlier years are detected and excluded. An overview of these results was presented in table 7 in the main text. In this table, we observe large negative and strongly significant return years for the years 1989, 2000 and 2002. Since the sample size of 1989 is only 2 observations and the effect is not too extreme, I won't exclude these observations from the analysis. For the years 2000 and 2002 however, the amount of observations as well as the negative effect is large enough to bias the overall loss effect. These years are excluded from the original analysis.

For my second outlier analysis I am using the Cook's distance measure to regress the model. Cook's distance is a commonly used estimate to detect the effect of outliers in a least squares regression. It is a measure introduced by Dennis Cook that incorporates the information of the residual and leverage of an observation (Cook, 1977). The leverage reflects the magnitude of the outlier in that particular observation. In the statistical test, the Cook's distance is calculated for each observation and dropped out if the outlier is too big. The regression is performed in STATA using `rreg` command, which uses the Cook's Distance estimate.