The mood beta concept of Hirshleifer, Jiang & Meng (2017) examined by incorporating soccer results.

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Summary

This thesis examines the mood beta concept of Hirshleifer, Jiang and Meng (2017) in which Hirshleifer et al. claim that a unique mood beta fully captures a stocks' sensitivity to mood. This thesis examines if such mood betas are significant by using a European instead of a U.S. sample, with stocks of companies included in the STOXX600. Moreover, this thesis also takes into account soccer results as an alternative measure of mood, in order to examine whether there is a correlation between the mood beta measured by calendar effects and the mood effect on stock prices caused by soccer results. If there is correlation, it can be concluded that the mood betas are indeed a valid measure of a stocks' sensitivity to mood. First, this thesis tests whether the mood betas are significant. However, mostly insignificant mood betas are found. Second, no correlation is found between the stock return responses after international soccer wins and losses and the insignificant mood betas. Overall, this thesis questions whether the mood beta concept of Hirshleifer et al. (2017) is really a valid measure of stocks' sensitivity to mood. However, the method could be valid but at least it can be concluded that the mood beta concept cannot be confirmed under all circumstances

Keywords: Mood beta, calendar effects, return persistence and reversal, soccer anomaly

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1. Introduction

It has been acknowledged that stock markets are inefficient, which implies that abnormal returns could be earned by deploying strategic trading strategies (Tucker et al., 2010). One important profitable trading strategy could be explained by seasonality of stock returns. This seasonality implies the periodic variation in the mean returns of market index portfolios and individual stocks (Hirshleifer, Jiang & Meng, 2017). Suggested is that investor mood contributes to the existence of these seasonalities. Conceptually, positive mood swings cause periodic optimism, and negative mood swings cause periodic pessimism. This results in seasonal variation in stock prices, which implies that there should be stock price predictability in corresponding positive and negative mood months. The concept that mood swings cause periodic optimism and pessimism which result in seasonal variation in stock prices have been documented. Moreover, researchers found out that stocks relatively outperform other stocks during the same calendar month (Heston and Sadka, 2008, 2010), but also on the same day of the week (Keloharju et al., 2016) or during the same pre-holiday period (Hirshleifer et al., 2016). Hirshleifer et al. (2017) argue that the relative outperformance of certain stocks could be explained by stocks' different sensitivity to investor mood. This implies basically that stocks with a high sensitivity to mood have both a higher return under positive mood swings, and a lower return under negative mood swings.

For now, the finding that stocks have different sensitivities to investor mood has only been investigated with calendar effects as the determinants of investor mood, like the January, October, Monday, Friday and pre-holiday effect. However, there could be several other variables which affect investor mood which lie beyond the origin of calendar effects. For example, Edmans, Garcia and Norli argue that there is a strong link between soccer results and investor mood (Edmans et al., 2007; Ashton et al., 2003, 2011; Scholtens & Peenstra, 2009). If evidence will show whether there are stocks which are more sensitive to soccer results, investors could anticipate to soccer results by buying the mood-sensitive stocks after positive soccer results and by (short)selling these specific stocks after bad soccer results. Basically, this would suggest that the mood beta concept also yields for other mood-influencing variables, like soccer results. Therefore, this thesis will investigate whether there are differences in stocks' sensitivity to soccer results, which could lead to future return

predictability and thus new profitable trading strategies. More specifically, this thesis will test whether the mood betas resulting from the approach of Hirshleifer et al. (2017) are correlated with the return response after soccer matches. If evidence will show that there is correlation between these coefficients, this evidence will support and strengthen the claim of Hirshleifer et al. (2017) that their estimated mood beta really indicates stocks' sensitivity to mood. In other words, the correlation would indicate that the stock return response after soccer wins or losses is in line with what would have been expected according to mood beta indication of stocks' sensitivity to mood.

This thesis is structured as follows. In chapter 2, the theoretical framework is presented. This chapter elaborates on the theory underlying the contents of this thesis. More specifically, paragraph §2.1 elaborates on the Efficient Market Hypothesis. Paragraph §2.2 explains the three forms of the EHM. Furthermore, paragraph §2.3 examines problems with the EMH. Subsequently, paragraph §2.4 examines factors which could cause the problems with the EMH by addressing insights of Behavioral Finance. Thereafter, paragraph §2.5 elaborates the requirements for mood variables to rationalize the link with stock returns. Finally, paragraph §2.6 examines the soccer anomaly and seasonality effects.

In chapter 3, the research problem is explained in paragraph §3.1. The hypotheses, which are built on the theory of chapter 2, are elaborated in paragraph §3.2. Subsequently, chapter 4 is about the data and research method used in this thesis. Paragraph §4.1 elaborates on the data, while paragraph §4.2 explains which research methods are used in order to form conclusions regarding the hypotheses of paragraph §3.2. Subsequently, the results are presented and explained in chapter 5. More specifically, paragraph §5.1 elaborates the calendar month seasonality effects, paragraph §5.2 examines the weekday seasonality effects, paragraph §5.3 is about mood beta and seasonality effects, paragraph §5.4 examines the soccer anomaly while paragraph §5.5 eventually examines the relation of the mood betas and the soccer anomaly.

When the results are examined, chapter 6 provides a summary and conclusive statements about the contents of this thesis. In the discussion in chapter 7, limitations of this thesis are examined. Finally, chapter 8 includes the bibliography, while in chapter 9 the appendix is addressed.

2. Theoretical framework

This chapter will provide an overview of the existing literature on the topics of this thesis. The theories and concepts explained in this section will form the foundation of this thesis on which the resulting hypotheses and analysis are built on. First, paragraph §2.1 elaborates on the Efficient Market Hypothesis. Consequently, paragraph §2.2 describes the three forms of the Efficient Market Hypothesis. Overall, if markets are efficient there is no possibility to outperform the market by deploying certain trading strategies. However, evidence shows that trading strategies deployed in order to outperform the market return actually do exist. Therefore, paragraph §2.3 elaborates on the problems with the EMH. Subsequently, paragraph §2.4 investigates the underlying causes of the inefficiency of financial markets, addressing insights of Behavioural Finance. Financial markets appear to be inefficient according to the EMH mainly due to the fact that people are involved in stock markets. These people have emotional biases, which causes prices to deviate from the rational expected price. However, it is not easy to observe and quantify the direct link of emotions and stock prices. Therefore, paragraph §2.5 examines requirements for mood variables to rationalize their link with stock returns. If a mood variable satisfies the requirements of paragraph §2.5, it is assumed that the link with stock prices is rationalized. Finally, paragraph §2.6 examines return seasonalities and the relation of soccer results with stock returns.

§2.1 Efficient Market Hypothesis

According to Hayek (1945), the only problem when economists try to construct a rational economic order is one of logic. The solution relies purely on logic because of the strong assumptions that are associated with formulated optimization problems. Firstly, one's reasoning should be based on a given, clear system of preference. Secondly, one should have access to all possible relevant information. Finally, one should fully understand this information. These assumptions are incorporated in economic models by creating mathematical optimization problems with marginal rates of substitution between factors, which lead to single optimal solutions. However, empirically these demarcated situations do not reflect the actual problems which society faces. Although the economic calculus which is used to approach logical problems could help in solving problems of the whole society, it is

unlikely that its results represent the choices each single person of the society faces. According to Hayek (1945), the fundamental difference in the economic problems each single person faces is their access and understanding of information. The knowledge or information which has to be used in economic problems does not exist in concentrated or integrated form, but rather exists as incomplete and contradictory parts which are possessed by unique individuals. Therefore, when constructing a rational economic order, the fundamental difficulty is how to make sure that all individuals possess the same amount of information or knowledge, and that each individual has the same understanding of this information.

By describing this fundamental difficulty, Hayek (1945) approached one of the main problems of the history of economic theory; what is the best system or mechanism of utilizing knowledge which initially is divided between individuals? Or in other words, what is the best way to design an efficient economic system? There are basically two ways to do the economic planning. One way is that planning has to be done centrally by a single authority, which has full authority over the whole economic system according to one unified plan. On the other hand, the planning could be divided over individuals, in which there is competition within each separate actor in the system. The main point of Hayek (1945) is that the problem how to utilize knowledge could be solved and in fact is being solved by price systems. More specifically, all the separate actions and thoughts of individuals are coordinated through pricing systems, with the result of one single price. This process is driven by the motivation of individuals to acquire and act on their private information in order to profit from it. If each individual acts this way, prices will be more and more efficient, leading to a market price which reflects all available information of individuals. The market price can only change if there is new information available to individuals (Hayek, 1945).

The point made by Hayek (1945) is relevant for this thesis since it argues that market systems are built on all the moods and emotions of individuals which result in a price. Overall, the arguments of Hayek (1945) are very closely linked to the Efficient Market Hypothesis. In fact, the article of Hayek could be seen as the predecessor of the Efficient Market Hypothesis. According to the Efficient Market Hypothesis (EMH), a market could be called “efficient” when the stock prices fully reflect all available information. This implies that it is impossible to outperform the market consistently, since market prices can only change due to new

information available and this new information is assumed to be rapidly processed in the stock prices (Malkiel & Fama, 1970). In 1960, Eugene Fama published an article in which he provides an answer to the question to what extent historical stock prices could be used in order to predict future stock prices. In that time, the consensus was that the past behaviour of stock prices should be a useful source of information concerning future stock prices. More specifically, the consensus was that price patterns of past stock prices will tend to persist in the future. This basically implies that by performing a careful analysis of past stock prices, one would be able to use this knowledge in their own advantage in order to increase profits (Fama, 1960). However, Fama (1960) finds that stock prices more or less follow a random walk, which he describes like: "*In statistical terms the theory says that successive price changes are independent, identically distributed random variables. Most simply this implies that the series of price changes has no memory, that is, the past cannot be used to predict the future in any meaningful way.*" (Fama, 1960, pp. 34). The controversial finding that historical stock prices are of no real value for investors implied that stock markets are efficient, what Fama later calls weak-form efficiency.

Fama further developed his research about the efficiency of stock markets and came up with the article entitled "Efficient Capital Markets: A Review of Theory and Empirical Work" which was published in the Journal of Finance in 1970. With this article he created the Efficient Market Hypothesis; basically this hypothesis argued that stocks always trade at their fair value, which is the price what would be expected rationally based on the information available. Whenever new information appears, investors update their beliefs and expectations accordingly. Even when these individuals update their beliefs irrationally, the Efficient Market Hypothesis works, in the sense that prices reflect their fair value. To be more precise, the EMH allows investors to overreact or underreact to news, and, on average, the net effect of the reactions of investors on stock prices follows a random normal distribution. This implies that the net effects of information on stock prices could not be used in order to make abnormal profits. However, this does not say that individuals which basically form the price are always right. Any person could be wrong about the market, but, on average, the views on the market as a whole lead to right market prices such that the market as a whole is always right (Malkiel & Fama, 1970).

§2.2 Forms of the Efficient Market Hypothesis

There are three forms of market efficiency according to the EMH. The first is weak-form efficiency, the second is semi-strong efficiency and the third is strong-from efficiency. Weak-form efficiency means that future prices could not be predicted correctly by only using historical prices. This implies that by analyzing past stock prices one is not able to produce excess returns, and that future prices are only dependent on information which is not incorporated in historical prices. If a market is efficient in the weak form, market participants are not able to systematically profit from market inefficiencies (Fama, 1960).

Subsequently, semi-strong efficiency implies that market participants cannot systematically produce excess returns by using publicly available information, since new publicly available information is very rapidly processed into stock prices. So neither analysis of historical information (technical analysis) or publicly available information (fundamental analysis) could systematically produce excess returns when markets are semi-strong efficient (Malkiel & Fama, 1970).

Finally, when markets are strong-efficient, stock prices reflect both publicly available information and private information and no investor could earn excess returns. The condition for markets to be strong-form efficient, is that insider information is made publicly known, otherwise only corporate managers could profit from this information (Malkiel & Fama, 1970).

§2.3 Problems with the Efficient Market Hypothesis

Fama, Fisher, Jensen and Roll (1969) found evidence in line with the EMH by conducting event studies with stock splits. Their research shows that markets are efficient in the sense of that stock prices rapidly adjust to new information. However, there are also researchers who found evidence against the EMH. In this paragraph, the problems with the EMH will be addressed.

In order to test the efficiency of markets, the Capital Asset Pricing Model is often used. The CAPM, created by William Sharpe, is a model which is used to determine the appropriate theoretical required rate of return of financial assets (Sharpe, 1964). By using this model, evidence is found against the EMH. For example, the observation that small stocks and stocks

with low book-to-market values earn higher returns than what could be explained by the Capital Asset Pricing Model, is a finding which is not in line with the EMH (Nicholson, 1968; Basu, 1977). Moreover, further tests of market efficiency led to the rejection of the CAPM (Gibbons, Ross & Shanken, 1989). These findings eventually led to the Fama-French three-factor model (Fama & French, 1993). In this model, Fama and French designed a model which explains stock returns with three risk factors. These risk factors include market risk, the outperformance of small versus big companies (SMB), and the outperformance of high book-to-market versus low book-to-market stocks (HML). However, contrary to the CAPM, which was built on modern portfolio theory, the Fama-French three-factor model is not based on modern portfolio theory but rather on empirically observed deviations of the EMH (Fama & French, 1993). This basically implies that the Fama-French three-factor model is better suited to describe a stock price process in reality, but it is not supported by modern portfolio theory.

However, there still is no consensus whether the CAPM is the right model to measure market efficiency. When evidence is found against the EMH by using the CAPM, two conclusions could be made. It could be that either markets are inefficient, or that the CAPM is the wrong model when measuring market efficiency. This dilemma is commonly known as the Joint Hypothesis problem or as the Roll's Critique (Roll, 1977). Although the Fama-French three-factor model is not in line with modern portfolio theory, it seems that this model provides evidence of the inefficiency of markets. The relevant question now is where this inefficiency comes from.

§2.4 Behavioral Finance

Economists like Fama and Malkiel argue that markets are efficient. However, a vast amount of literature shows that trading strategies which consistently outperform the market do exist, which implies that markets are inefficient according to the Efficient Market Hypothesis. More research towards this inefficiency led to new insights in economics and a new sub-field in economics was created; Behavioural Finance.

Behavioural finance researchers are focussed on the effects of emotional, cognitive, psychological and social factors on economic decision making, since these decisions eventually affect market prices and stock returns. Overall, economics has always relied on principles of rationality in order to be able to model human behaviour (Davis, 2008). However, rationality

is a normative concept or a prescription of how one is ought to act but does not describe peoples' decision making (Friedman, 2015). The essential reason why behavioural insights are relevant for economics, is the fact that people show irrational behaviour, which is called 'bounded rationality' according to Herbert Simon (Sent, 2006). The observation that people act far from rational made economic modelling less relevant, since they assume rational and maximizing behaviour (Van Damme, 1999). Therefore, behavioural economics tries to increase the explanatory power of economic models and theories by means of providing models and theories with more realistic psychological foundations. This improves the field of economics by generating theoretical insights, by suggesting better policy and by making better predictions of field regularities (Camerer and Loewenstein, 2004).

However, this does not mean that neoclassical theories and mathematical economic models are considered to be useless due to its unrealistic assumptions. According to Camerer and Loewenstein (2004), those models and theories are still useful in the sense of that they provide economists with a theoretical framework, which could be applied in explaining various forms of economic behaviour. Nevertheless, economics always rests on psychology since there is human involvement in economics (Eichner, 1983). This human involvement is associated with humans' bounded rationality, which makes economics a normative, hence a social science instead of a natural science. Human involvement is the essential reason for markets to be inefficient according to the criteria of the Efficient Market Hypothesis.

Thus, the deviations from rational prices are a result of humans cognitive and emotional biases. Emotional biases are caused by emotions and mood. According to Forgas (1995, p. 41), mood could be defined as "*low-intensity, diffuse and relatively enduring affective states without a salient antecedent cause end therefore little cognitive content (e.g. feeling good or feeling bad)*". In turn, emotions are "*more intense, short-lived and usually have a definite cause and clear cognitive content like anger or fear*" (Forgas, 1995, p. 41). This basically means that moods may have a potentially more enduring influence on people's cognitive processes compared to emotions. However, since emotions often have a more clear root cause, emotions are more interesting for behavioural finance research since the specific events that trigger emotions could be directly placed in relation with relevant topics like explaining stock returns (Forgas, 1995).

However, individual investor mood or emotion is less relevant for research about stock prices, since one individuals' mood could not affect the aggregate stock market. Social mood is more relevant according to Olson (2006), which could be described as a collective manifestation of individual mood and emotions. Individual emotions lead to a social mood by contagion, which implies that individual moods affect each other by pushing towards the same mood (Olson, 2006). On the other hand, the general mood in the society affects the mood of individuals, which impacts important investment decisions (Nofsinger, 2005). Basically this implies that social mood influences individuals' mood and vice versa.

§2.5 Requirements for mood variables to rationalize its link with stock returns

Now it is clear what the Efficient Market Hypothesis implies and what the main underlying cause of markets to be inefficient is, the link of peoples' emotions on stock prices has to be clarified.

Overall, financial markets appear to be inefficient according to the EMH mainly due to the fact that people are involved in stock markets. These people have emotional biases, which causes prices to deviate from the rational expected price. However, it is not easy to observe and quantify the direct influence of emotions on stock prices. Therefore, Edmans et al. (2007) came up with three key characteristics to rationalize studying the link of social mood and stock returns. The first assumption is that the given variable for mood must drive mood in a substantial and unambiguous way, so that its effect is powerful enough to show up in asset prices. The second assumption is that the variable that should indicate mood must impact the mood of a large proportion of the population, so that it is likely to affect enough investors. Finally, the third assumption is that the effect of mood must be correlated across the majority of individuals within a country. Basically, if a mood variable satisfies these three criteria, research about the impact of such a mood variable on the stock price is justified.

§2.6 The soccer anomaly and seasonality effects

Now it is made clear to which criteria a mood variable should meet in order to justify research about the effects of mood on the stock price, two variables which could proxy mood are assessed in order to find out to what extent they could be perceived as mood variables. The first effect which is examined is the soccer results effect, while the second are calendar effects.

According to Edmans et al. (2007), international soccer results satisfy the three criteria presented in paragraph §2.5. The underlying thought of the link of international soccer results and social mood is investigated by psychologists, which concluded that sport results in general have a significant effect on mood. Basically, people experience a strong positive reaction when their team performs well but experience a negative reaction after a bad performance. Moreover, these positive and negative reactions affect peoples' self-esteem both positively and negatively, and affect feelings about life in general (Wann et al., 1994). However, soccer results should not only affect feelings about life in general but also economic behaviour. Arkes et al. (1988) have found evidence that the victory of the Ohio State Universities' football team increased the sales of the Ohio State lottery tickets, which implies that the sport result initiated optimism, which eventually led to increased economic behaviour and risk taking.

Overall, it could be concluded that international soccer results could be used to proxy investor mood. Edmans et al. (2007) documented a significant market decline after soccer losses. Moreover, this loss effect is stronger in small stocks and in more important games. However, Edmans et al (2007) have not found evidence that improvements in mood after soccer wins affected stock markets. This implies that the impact of losses is higher than the impact of wins. This is in line with the idea of Kahneman and Tversky (1979, 1992) that losses loom larger than gains.

Apart from soccer results there are alternative determinants which have an influence on investor mood and also on stock returns, for example weather conditions (Hirshleifer & Shumway, 2003) or sudden celebrity deaths (Chen, 2011). However, it is not the scope of this thesis to sum up all these different determinants. Besides soccer results as a proxy for mood, this thesis examines another proxy for mood which is commonly described as return seasonality or as calendar effects. As mentioned in paragraph §2.5, it has been acknowledged that stock markets are inefficient, which implies that abnormal returns could be earned by

deploying strategic trading strategies (Tucker et al., 2010). One important profitable trading strategy is built on the finding that there is seasonality of stock returns. This seasonality implies that there is periodic variation in the mean returns of market index portfolios and individual stocks (Hirshleifer, Jiang & Meng, 2017). Suggested is that investor mood contributes to the existence of these seasonalities. Conceptually, positive mood swings cause periodic optimism, and negative mood swings cause periodic pessimism. This results in seasonal variation in stock prices, which implies that there should be stock price predictability in corresponding positive and negative mood periods. In fact, researchers found out that stocks relatively outperform other stocks during the same calendar month (Heston and Sadka, 2008, 2010), but also on the same day of the week (Keloharju et al., 2016) or during the same pre-holiday period (Hirshleifer et al., 2016). Such effects are called calendar effects. For example, according to Hirsleifer et al. (2017), the January, Friday and the pre-holiday effect represent positive mood periods. In contrast, the September/October, Monday and the post-holiday effect represent negative mood periods. Hirshleifer et al. (2017) find that relative overperformance across stocks during positive mood periods tends to persist in future periods with positive mood, which is called return persistence. In the next chapter, the knowledge about return seasonalities and about the soccer anomaly are brought together, leading to this thesis´ research problem and research question in paragraph §3.1. In paragraph §3.2 the hypotheses which will be tested in this thesis are elaborated.

3. Research problem and hypotheses

§3.1 Research problem

As mentioned in paragraph §2.6, relative performance of stocks tends to persist in future periods with positive mood. However, relative performance also tends to reverse in periods with negative mood, which is called return reversal. This implies that stocks react to mood in a proportional way, and that there could be differences in sensitivity to mood between stocks.

Hirshleifer et al. (2017) test the hypothesis that each stock has a unique sensitivity to mood. They found that stocks with higher mood betas estimated during seasonal windows of strong moods earn higher expected returns during positive mood periods, but lower returns during negative mood seasons. They also found that this pattern tends to hold in the future. It is interesting to see whether the concept of mood betas could also be applied to mood shocks induced by other factors than calendar effects. When research finds out that indeed each stock has a unique mood beta and that this mood beta really captures a stocks´ sensitivity to mood, new profitable trading strategies could be exploited by for example determining mood-sensitive stocks and buying these stocks in positive-mood periods.

For now, the finding that stocks have different sensitivities to investor mood has only been investigated with calendar effects as the determinants of investor mood, like the January, October, Monday, Friday and pre-holiday effect. It is interesting to see whether mood swings induced by soccer results could cause periodic optimism or pessimism, which eventually results in periodic mispricing of stocks. New profitable trading strategies could be exploited if evidence of periodic mispricing due to soccer results could be found. Moreover, this trading strategy could be even more profitable if research will deliver evidence of stocks that relatively outperform other stocks, given the same mood shock induced by soccer results. In other words, if evidence will show whether there are stocks which are more sensitive to soccer results than other stocks, investors could anticipate to soccer results by buying the mood-sensitive stocks after positive soccer results and by (short)selling these specific stocks after bad soccer results. Therefore, this thesis will investigate whether there are differences in stocks' sensitivity to soccer results, which could lead to future return predictability and thus a new profitable trading strategy. More specifically, this thesis will test whether the mood betas resulting from the approach of Hirshleifer et al. (2017) are correlated with the return response

after soccer matches. If evidence will show that there is correlation between these coefficients, it could be concluded that the claim of Hirshleifer et al. (2017) that their estimated mood beta really indicates stocks' sensitivity to mood is legit. In other words, the correlation would indicate that the stock return response after soccer wins or losses is in line with what would have been expected according to mood betas indication of sensitivity to mood. The research question of this thesis is:

"Does the mood beta concept of Hirshleifer, Jiang and Meng (2017) deliver mood betas which really reflect stocks' sensitivity to mood when controlling for soccer results effects?"

Expected is that stocks with higher mood betas react more heavily on mood shocks induced by soccer results compared to stocks with lower mood betas. For now, the mood beta holds only for seasonality of stock returns. Existing literature has not yet investigated whether the mood beta concept holds for the effect of soccer results, or with a different stock sample. Therefore this research question is a novel one, with a clear contribution, since this thesis could contribute to the existing literature in a way that it will provide evidence whether the mood betas calculated by Hirshleifer et al. (2017) actually represent mood rather than just calendar effects. If this thesis shows that stocks with a higher mood sensitivity are also more sensitive for mood shocks induced by soccer results rather than calendar effects, the evidence for the existence of mood betas will become stronger and short-term traders could try to profit from this thesis' finding. Overall, this thesis could strengthen Hirshleifer et al. (2017) by adding soccer results as a determinant of mood. Moreover, this thesis tests whether mood betas are significant over an European sample rather than over a U.S. sample. If significant mood betas are to be found, the findings of Hirshleifer et al. (2017) are more robust. However, this thesis is also able to question Hirshleifer et al. (2017), when either insignificant mood betas are found, or when the significant mood betas are found but they do not interact with the coefficients for soccer wins and losses. In that case, the mood betas do not really reflect stocks' sensitivity to mood.

§3.2 Hypotheses

In this paragraph, the hypotheses which will be tested in this thesis will be elaborated. First of all, this thesis will test whether there is a same-month return persistence effect for the months

January and September. Additionally, this is also tested for October for robustness. Hypothesis 1 is as follows:

H1: The lagged same-month return is positively related to the current same-month return, which implies that relative performance of stocks persists during the same calendar month, year after year.

Subsequently, this thesis will test whether there is return reversal in incongruent-mood months. The hypothesis concerning this return reversal is as follows:

H2: A cross-sectional return reversal effect takes place across the two calendar months with expected incongruent mood-states proxied by January and September, for at least a few year after year. This implies that the lagged incongruent-mood month returns are negatively related to the incongruent-month return.

Next, this thesis will test whether there is return persistence across same-weekday returns, and whether there is return reversal across incongruent-weekday returns when Monday is assumed to be the negative-mood day and Friday is assumed to be the positive-mood day. The associated hypotheses are as follows:

H3: The lagged same-day return is positively related to the current same-day return, which implies that relative performance of stocks persists during the same day, week after week.

H4: A cross-sectional return reversal effect takes place across two days with expected incongruent mood-states, week after week. This implies that the lagged incongruent-mood day returns are negatively related to the incongruent-day return.

The first four hypotheses are individually tested in order to provide a clear structure to this thesis. Based on Hirshleifer et al. (2017), it is expected that historical seasonal returns of a security will be positively related to its future seasonal returns under a congruent mood state, and negatively related to its future seasonal returns under an incongruent mood state.

Furthermore, the mood betas estimate stocks' sensitivity to mood shocks. More specifically, mood beta measures a stocks' average return increase (decrease) in response to a percentage point increase (decrease) in the aggregate market return induced by strong mood fluctuations. More elaboration about how the mood betas are estimated is presented in paragraph §4.2. The hypothesis concerning the mood betas is as follows:

H5: Mood beta is a positive predictor of the cross-section of stock returns during positive mood states and a negative predictor during negative mood states.

Now this thesis moves to the hypotheses of the relation between soccer results and stock returns. Based on paragraph §2.6, hypothesis 6 is as follows:

H6: International soccer results do have an influence on stock returns through moods and emotions. More specifically, soccer wins lead to a positive stock market reaction while losses lead to a negative reaction.

Finally, the hypothesis for main contribution of this thesis could be elaborated. Hypothesis 7 tests whether there is correlation between the mood betas estimated using calendar effects and the coefficients of soccer wins and losses. The hypothesis is as follows:

H7: There is a positive correlation between the mood betas and the coefficients for soccer wins, and a negative correlation between the mood betas and the coefficients for soccer losses.

Hypothesis 7 implies that the higher the mood beta, the higher the stocks' sensitivity to mood, the higher the coefficient for soccer wins and the more negative the coefficient of soccer losses. For robustness, this thesis also controls for the influence of the type of game, and whether a country is a soccer country. The associated hypotheses are as follows:

H8: The soccer anomaly is stronger for elimination games.

H9: The soccer anomaly is stronger for soccer countries.

4. Data and research method

In this chapter, the data and the research method which are used in order to test the hypotheses of Chapter 3 are described and explained in paragraph §4.1 and §4.2. More specifically, paragraph §4.1 elaborates on both the stock prices data and the soccer results data. After the data is discussed, paragraph §4.2 elaborates on the research method.

§4.1 Data

First of all, the stock price data which is used in this thesis consists of the 600 companies of the STOXX Europe 600 Index. This index includes large, mid and small capitalization stocks of firms across 17 countries of Europe, which are presented below:

COUNTRY	NUMBER OF FIRMS
AUSTRIA	7
BELGIUM	15
CZECH REPUBLIC	2
DENMARK	22
FINLAND	16
FRANCE	84
GERMANY	72
IRELAND	7
ITALY	31
LUXEMBOURG	3
NETHERLANDS	28
NORWAY	12
PORTUGAL	3
SPAIN	30
SWEDEN	44
SWITZERLAND	50
UNITED KINGDOM	174
TOTAL	600

The monthly and daily stock data of the STOXX Europe 600 Index is downloaded by Thomson Reuters Eikon. The monthly data was available from January 1973 till May 2017, and the daily data has a time range of 1 January 1965 - 28 April 2017. However, not only the daily and monthly stock returns are needed, but also excess returns have to be calculated. These excess returns could not be extracted from Thomson Reuters Eikon and have to be calculated by

subtracting the risk-free rate from the raw return. Therefore, the risk-free rate has to be specified. Normally, the US 10-year Treasury Yield would be used for defining the risk-free rate. However, the stocks in this thesis' dataset are of European origin so a European measurement for the risk-free rate would make more sense. Therefore this thesis assumes that the German 3-year bond yield represents the risk-free rate of Europe. This choice is built upon two reasons. Firstly, this thesis assumes that when the bond yield with a maturity of 3 years is used as risk-free rate, the resulting excess returns are a better representation for excess returns than when the bond yield with a maturity of 10 years is used. The 10-year bond yield is, on average, higher than the 3-year bond yield, which leads to mostly negative daily excess returns. When the 3-year bond yield is used, positive and negative daily excess returns are more in balance which is a better reflection of the reality. Secondly, the 3-year bond yield of Germany is chosen since Germany is the major country in the European Union. Subsequently, this thesis assumes that the MSCI Europe Index represents the market return, which is needed for estimating mood betas.

In order to test whether national teams' soccer results have an effect on stock prices, national teams' soccer results are required. These results are obtained from van den Heuvel (2014). Only the national soccer results of countries which have companies included in the STOXX Europe 600 Index are required, since the goal of this thesis is to test whether stocks react in line with their unique mood beta to mood shocks induced by soccer results. This means that the national teams' soccer results of only the 17 European countries presented at the previous page are included, instead of the 44 countries Edmans et al. (2007) use.

§4.2 Research method

In this section, the methodology and method of this thesis is elaborated. This thesis basically combines the approaches of two articles; the article of Hirshleifer et. al (2017) and the article of Edmans et al. (2007). Firstly, the approach of Hirshleifer et al. (2017) could be briefly explained as an approach which is used in order to test whether there is a the same-mood month/day return persistence effect and an incongruent-mood month/day return reversal effect. They find that relative stock performance during positive mood periods tend to persist in future positive mood periods, and tend to reverse in negative mood periods. Consequently,

Hirshleifer et al. (2017) create a unique mood beta for each stock, and tests whether this mood beta is significant and thus a predictor of a stocks' sensitivity to mood. They find that stocks with higher mood betas have higher returns in positive mood periods, but, however, earn lower returns during future negative mood seasons, which implies that high mood beta stocks are more sensitive to mood compared to low mood beta stocks. It is interesting to investigate whether these companies' unique mood beta is also a predictor of a stocks' sensitivity to mood when the mood shock is induced not by calendar effects but by international soccer results. If there is significant interaction with the soccer results effect and mood beta, this thesis strengthens the article of Hirshleifer et al. (2017) that each stock has a unique sensitivity to mood shocks.

Overall, Hirshleifer et al. (2017) use pretty straightforward regressions in order to investigate the return persistence and reversal effects and to create and test the significance of the mood betas. Therefore, this thesis assumes that it is more practical to show the regressions in chapter 5 (Analysis and Results), directly followed up by the regression results and their implications. However, the approach of Edmans et al. (2007) needs more attention. Therefore, the second part of the methodology of this thesis is about how to investigate the effect of a national team's soccer results on stocks of companies with the same national origin. The null hypothesis is that stock markets are unaffected by the outcomes of soccer matches. This implies that investors are rational, that stock markets are efficient and the economic benefits for companies associated with wins are unable to affect stock markets.

On the other hand, hypothesis 6 states that the effect of a national team win on the stock return of companies in that corresponding country is positive, while the effect of a loss is negative. This thesis uses the approach of Edmans et al. (2007) to estimate the impact of wins and losses with the following regression:

$$R_{i,t} = \gamma_{0,i} + \gamma_{1,i}R_{i,t-1} + \gamma_{2,i}R_{m,t-1} + \gamma_{3,i}R_{m,t} + \gamma_{4,i}R_{m,t+1} + \gamma_{5,i}D_t + \gamma_{6,i}Q_t + \varepsilon_{i,t}, \quad (1)$$

where $R_{i,t}$ is the daily return of stocks of companies in country *i* with day *t*, $R_{i,t-1}$ is the lagged company return, $R_{m,t-1}$ is the lagged market return (MSCI Europe), $R_{m,t}$ is the daily market return, $R_{m,t+1}$ is the lead market return, $D_t = \{D_{1t}, D_{2t}, D_{3t}, D_{4t}\}$ are dummy variables for Monday, Tuesday, Wednesday and Thursday and $Q_t = \{Q_{1t}, Q_{2t}, Q_{3t}, Q_{4t}, Q_{5t}\}$ are dummy

variables included for days for which the previous 1 through 5 days are non-weekend holidays (and thus non-trading days).

First of all, the lagged return $R_{i,t-1}$ is included into the regression. This is done in order to account for first-order serial correlation, which implies that errors in one period are correlated directly with errors in future periods (Born & Breitung, 2016). On top of that, there could be stock return correlation across countries and its stock markets (Edmans et al. 2007). Therefore the return of the market (MSCI Europe), $R_{m,t}$, is included in order to control for stock return correlation across countries. However, it could be that some stock markets do not interact simultaneously with the Europe's market index. This implies that some major stock markets might be leading the market index while minor stock markets are lagging the market index. To account for this, the lagged market return $R_{m,t-1}$ and the leaded market return $R_{m,t+1}$ are included in the model. Subsequently, $D_t = \{D_{1t}, D_{2t}, D_{3t}, D_{4t}\}$ are dummy variables which are included since they account for day-of-the-week effects, like the Monday and Friday effect, explained in chapter 2. Finally, $Q_t = \{Q_{1t}, Q_{2t}, Q_{3t}, Q_{4t}, Q_{5t}\}$ are dummy variables in order to control for non-weekend holidays, since these days are not trading days. To illustrate; if there is a non-weekend holiday, the first five days hereafter are identified as $\{Q_{1t}, Q_{2t}, Q_{3t}, Q_{4t}, Q_{5t}\}$ with a 1 for Q_{1t} for the first day, a 1 for Q_{2t} for the second day after a non-weekend holiday and so on.

However, Edmans et al. (2007) normalize stock returns since stock returns have time-varying volatility, while regression (1) assumes that there is constant volatility. Time-varying volatility could be simply explained as fluctuations in volatility over time, which implies that the standard deviation of stock returns is subject to large swings of high and low volatility (Schwert, 1989). These high and low volatility periods could harm the strength of thesis' results, since they bias the standard errors resulting from regression (1) and therefore eventually bias the significance of the soccer results wins and losses. In line with Edmans et al. (2007), this thesis therefore uses the GARCH (Generalized AutoRegressive Conditional Heteroskedasticity) model in order to model stock return volatility. By using this approach the heterogeneity in volatility across stocks will be eliminated and the GARCH model also corrects for time-series variation (Engle, 1982; Bollerslev, 1986). The process of the normalization of stock returns consists of 3 steps.

In the first step, regression (1) is run for each company separately in order to obtain the predicted conditional variances. Secondly, the returns are divided by the square root of the predicted conditional variance. In step 3, by using the command "egen" in Stata the mean is automatically subtracted from the return and divided by the standard deviation.

The created normalized returns are used when running regression (1), in order to estimate the residuals. After running regression (1), the Stata command "predict yhat" is used. The residuals are created by subtracting yhat, which represents the predicted return from regression (1), from the observed, normalized return. This implies that the residuals can be perceived as abnormal return. These residuals are of key importance when estimating the effects of soccer wins and losses.

Now the residuals $\varepsilon_{i,t}$ are known, they will function as the dependent variable in the following regression:

$$\varepsilon_{i,t} = \beta_0 + \beta_{Win} W_{i,t} + \beta_{Loss} L_{i,t} + u_{i,t} \tag{2}$$

where $W_{i,t} = \{W_{1i,t}, W_{2i,t}, \dots,\}$ are dummy variables for soccer wins, $L_{i,t} = \{L_{1i,t}, L_{2i,t}, \dots,\}$ are dummies for soccer losses. By performing this regression, β_{Win} and β_{Loss} show the effect of wins and losses on the residuals, i.e. the abnormal returns. This regression could test the hypothesis of chapter 3, which states that soccer wins have a positive effect on stock returns while soccer losses have a negative effect.

Finally, the major contribution of this thesis could be examined. As mentioned before in paragraph §4.2, Hirshleifer et al. (2017) create a unique mood beta for each stock, and test whether this mood beta is significant and thus a predictor of a stocks' sensitivity to mood. Like Hirshleifer et al. (2017), this thesis also creates unique mood betas for stocks while using a different database. As mentioned before, more elaboration about the mood betas is addressed in chapter 5.

Ultimately, the goal of this thesis is to check whether these unique mood betas are correlated with the soccer betas, and thus are indeed a predictor of a stocks' sensitivity to mood. This will be tested by adding interaction variables to regression (2), which makes it a multilevel model:

$$\varepsilon_{i,t} = \beta_0 + \beta_{Win} W_{i,t} + \beta_{Loss} L_{i,t} + \{\beta_i^{Win} * \beta_i^{Mood}\} + \{\beta_i^{Loss} * \beta_i^{Mood}\} + \varepsilon_{i,t} \tag{3}$$

where $\{\beta_i^{Win} * \beta_i^{Mood}\}$ is the interaction variable which consists of the unique company coefficient β_{Win} resulting from regression (2), multiplied by the unique company mood beta. $\{\beta_i^{Loss} * \beta_i^{Mood}\}$ is an interaction term consisting of β_{Loss} and the unique mood beta. If the interaction variables are significant, it could be concluded that the mood betas are indeed a measure of a stocks' sensitivity to mood since the soccer effects and the mood betas are correlated. In order to strengthen this conclusion, regression (3) is supplemented with two more interaction variables for robustness. The first is whether a country is a soccer country, while the second is an interaction variable which captures the influence of the type of game (group game or elimination game). These two interaction variables will be elaborated more in paragraph §5.5.

5. Analysis and results

In this chapter the data will be processed like described in the research method paragraph §4.2 and the results are presented and explained. As mentioned in chapter 4, this thesis has chosen to show the regression models concerning the approach of Hirshleifer et al. (2017) in this chapter. By doing so, the regression results could be shown directly after the regressions, which makes its implications directly clear and relevant.

The structure of this chapter is as follows. Paragraph §5.1 is about calendar month seasonality effects, in which §5.1.1 elaborates on the same-month return persistence effect and §5.1.2 examines the incongruent-mood month return reversal effect. Subsequently, paragraph §5.2 is about weekday seasonality effects. More specifically, §5.2.1 is about the same-weekday return persistence effect, while §5.2.2 is about the incongruent-weekday return reversal effect. Thereafter, paragraph §5.3 elaborates on mood beta and return seasonality, of which §5.3.1 is about mood beta and calendar month seasonality effects while §5.3.2 is about mood beta and weekday seasonality effects. Subsequently, paragraph §5.4 is about the influence of soccer results on stock prices. Finally, paragraph §5.5 tests the relation between mood beta and the soccer anomaly.

§5.1 Calendar month seasonality effects

§5.1.1 The same-month return persistence effect

This paragraph tests the same-calendar-month persistence effect which was first documented by Heston and Sadka (2008). This is done by running Fama-MacBeth (FMB) regressions of the January and September returns across stocks on their historical same-month returns at the 1st to the 10th annual lag. Hirshleifer et al. (2017) use October instead of September returns, in which October is assumed to be the negative mood month. However, the monthly stock return data of this thesis shows that September is the negative mood month instead of October, when looking to the mean returns presented in Table 1 in Appendix A. Therefore this thesis assumes September to be the negative mood month. The first FMB regression looks as follows:

$$RET_{\text{Jan(Sep)},t} = \eta_{k,t} + \gamma_{k,t} RET_{\text{Jan(Sep)},t-k} + \varepsilon_t \qquad (4)$$

in which k = 1, …, 10, $RET_{\text{Jan(Sep)}}$ is the current January or September return in year t for a given stock and $RET_{\text{Jan(Sep)},t-k}$ is the historical January or September return in year t-k for the same stock. The regression results of the same-month return persistence effect for January are presented in Table 1 below, in which the return of January is the dependent variable and the ten lagged returns of January are the independent variables.

Table 1: The same-month return persistence effect for January.

	(1) FMB	(2) FMB - influential outliers
lag1RETjan	0.0544**	0.0522**
	(2.38)	(2.30)
lag2RETjan	0.0220	0.0195
	(0.98)	(0.85)
lag3RETjan	0.0163	0.0133
	(0.84)	(0.73)
lag4RETjan	-0.0129	-0.0115
	(-0.61)	(-0.54)
lag5RETjan	0.0251*	0.0258*
	(1.76)	(1.79)
lag6RETjan	0.0120	0.0122
	(0.70)	(0.72)
lag7RETjan	0.0393**	0.0390**
	(2.22)	(2.20)
lag8RETjan	-0.0139	-0.0139
	(-0.90)	(-0.90)
lag9RETjan	0.0136	0.0118
	(1.19)	(1.08)
lag10RETjan	0.0161	0.0183
	(1.01)	(1.17)
_cons	0.0167**	0.0166**
	(2.18)	(2.17)
N	9450	9444

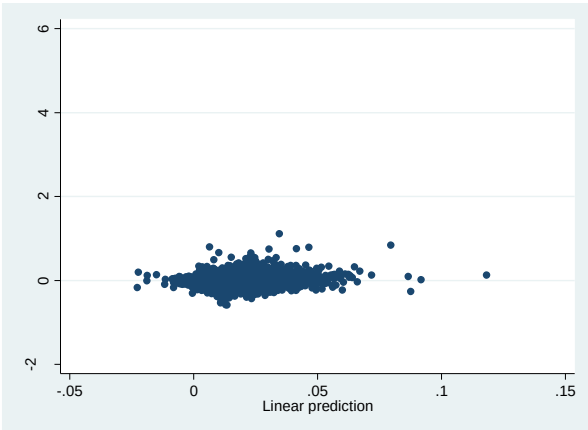
t statistics in parentheses
* p<0.1, ** p<0.05, *** p<0.01

From Table 1 it could be concluded that the first, fifth and seventh lagged January return have a positive, significant effect on the current January return. Especially the return of January of one year ago has a strong, positive effect on the current January return. In order to illustrate; for the first annual lag the coefficient is 0.0544 (t-value = 2.38). This implies that a one-standard-deviation (0.0229) increase in the prior same-month return increases the current

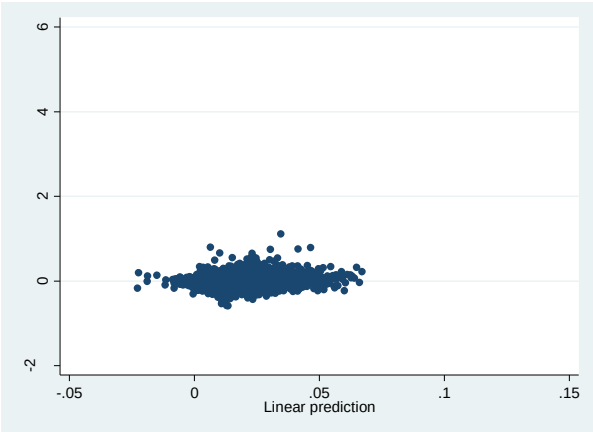
same-month return with 0.0544 * 0.0229 = 0.125 percent. Overall, Table 1 provides evidence of the same-month return persistence effect for January for the first, fifth and seventh lag. This is in line with hypothesis 1, but, however, Hirshleifer et al. (2017) find positive, significant coefficients for all ten lags. Although this thesis confirms the same-month return persistence effect for January, the results are less robust compared to the results of Hirshleifer et al.

It is worth mentioning that when regression (4) is performed after removing influential outliers of RET_{Jan}, the regression results overall became even a bit less significant. The regression results are visible in Table 1 column (2): FMB – influential outliers. In order to detect influential outliers, the Stata command "predict cook" is used and this resulted in five influential outliers, which are visible Graph 1 below and removed in Graph 2.

Graph 1: RETjan



Graph 2: RETjan without I.O.



Moreover, the same-month return persistence effect for January is additionally also estimated using OLS, GLS and FE regressions for robustness. The results are presented Table 1 in Appendix B. However, these results are of minor importance since according to Fama & MacBeth (1973), the appropriate way to test whether stocks have return seasonality effects is by performing FMB regressions. Such regressions are made up of two steps: in the first step, for each single time period a cross-sectional regression is performed. In the second step, the returns are regressed against the coefficients of the first step in order to determine the risk premia. However, the FMB standard errors only correct for cross-sectional correlation, but not for time-series correlation. According to Fama & French (1988) time-series correlation could be a problem over longer holding periods. The FMB standard errors could be corrected by Newey & West (1987) standard errors, however in that case Stata is unable to test for

significance in the coefficients, while their significance is required. Therefore only FMB standard errors are used in this thesis.

Consequently, Table 2 below shows the same-month return persistence effect for September. Column (1) shows the FMB coefficients while column (2) shows the coefficients when the influential outliers are deleted (see Graph 1 & 2 in Appendix B). Only the fourth and fifth lagged September return have a significant effect on the dependent variable current September return. It is interesting to see that the fourth lagged September return has a negative effect, which is in conflict with hypothesis 1. Based on the results of Table 2, this thesis could confirm the same-month return persistence effect for September only for the fifth lag. Overall it could be concluded that hypothesis 1: *"The lagged same-month return is positively related to the current same-month return, which implies that relative performance of stocks persists during the same calendar month, year after year."* can be confirmed only for some lags, so the evidence is not as strong as the evidence of Hirshleifer et al. (2017).

Table 2: The same-month return persistence effect for September.

	(1) FMB	(2) FMB - influential outliers
lag1RETsep	0.0254	0.0251
	(0.91)	(0.90)
lag2RETsep	-0.0270	-0.0271
	(-1.40)	(-1.40)
lag3RETsep	-0.0111	-0.0112
	(-0.60)	(-0.61)
lag4RETsep	-0.0323**	-0.0324**
	(-2.44)	(-2.44)
lag5RETsep	0.0415***	0.0415***
	(3.13)	(3.13)
lag6RETsep	-0.0232	-0.0233
	(-1.39)	(-1.40)
lag7RETsep	0.0197	0.0197
	(1.07)	(1.07)
lag8RETsep	0.0160	0.0161
	(0.88)	(0.88)
lag9RETsep	0.0120	0.0121
	(0.79)	(0.79)
lag10RETsep	0.0070	0.0070
	(0.61)	(0.61)
_cons	-0.0047	-0.0047
	(-0.68)	(-0.68)
N	9196	9193

t statistics in parentheses
* p<0.1, ** p<0.05, *** p<0.01

§5.1.2 Incongruent-mood month return reversal effect

This section will elaborate on the cross-sectional reversal effect across incongruent mood months. This effect will be tested with the use of the following FMB regression:

$$RET_{\text{Jan(Sep)},t} = \eta_{k,t} + \gamma_{k,t} RET_{\text{Sep(Jan)},t-k} + \varepsilon_t \quad (5)$$

The regression above regresses the return of January (September) on the incongruent mood-month return of September (January). Expected is that an increase in last incongruent-month return leads to a return decrease in the subsequent return of January/September. If the coefficient is significant, this implies that there is evidence of a cross-sectional reversal effect across two calendar months with incongruent mood states. In Table 3 and 4 on the next page the regression results are shown. For robustness, the regressions are also performed for the return of October (which Hirshleifer et al. (2017) use) instead of September, in which both January and October and September and October should represent incongruent mood-months.

From Table 3, it could be concluded that there is no incongruent-mood-month return reversal effect. Although the first and second lagged January return coefficients are negative, which is in line with expectations, the lagged January returns are not able to significantly explain the return in September or October. It is worth mentioning that the first lagged January return represents the return of January of the same year as the return of September and October.

On the other hand, Table 4 suggests that there is an incongruent-mood-month return reversal effect for the third and fourth lagged September return. The coefficients of these variables are negative and significant at the 1% level. However, the coefficients for the other eight lagged January returns are also negative but insignificant. Recall, the hypothesis concerning the incongruent-mood month return reversal effect is as follows:

H2: A cross-sectional return reversal effect takes place across the two calendar months with expected incongruent mood-states proxied by January and September, for at least a few years. This implies that the lagged incongruent-mood month returns are negatively related to the incongruent-month return.

Table 3: Incongruent-mood-month return reversal effect.

	(1) RETsep	(2) REToct
lag1RETjan	-0.0146	-0.0064
	(-0.93)	(-0.37)
lag2RETjan	-0.0127	-0.0001
	(-0.68)	(-0.01)
lag3RETjan	0.0110	0.0063
	(0.56)	(0.34)
lag4RETjan	0.0295	-0.0097
	(1.57)	(-0.65)
lag5RETjan	-0.0160	-0.0219
	(-1.00)	(-1.23)
lag6RETjan	0.0023	0.0224
	(0.14)	(0.97)
lag7RETjan	0.0015	0.0113
	(0.10)	(0.70)
lag8RETjan	0.0037	-0.0117
	(0.33)	(-0.89)
lag9RETjan	-0.0073	-0.0041
	(-0.53)	(-0.25)
lag10RETjan	0.0066	0.0084
	(0.46)	(0.54)
_cons	-0.0085	0.0134
	(-1.09)	(1.46)
N	8933	9450

t statistics in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Table 4: Incongruent-mood-month return reversal effect.

	(1) RETjan	(2) REToct
lag1RETsep	-0.0057	-0.0047
	(-0.20)	(-0.19)
lag2RETsep	-0.0271	0.0309
	(-1.29)	(1.50)
lag3RETsep	-0.0611***	0.0053
	(-3.37)	(0.26)
lag4RETsep	-0.0599***	0.0242
	(-3.20)	(1.28)
lag5RETsep	-0.0117	0.0052
	(-0.61)	(0.32)
lag6RETsep	-0.0382*	0.0178
	(-1.93)	(0.84)
lag7RETsep	0.0095	0.0168
	(0.49)	(0.91)
lag8RETsep	0.0118	-0.0082
	(0.61)	(-0.53)
lag9RETsep	-0.0229	-0.0146
	(-1.44)	(-1.10)
lag10RETsep	0.0090	-0.0024
	(0.43)	(-0.17)
_cons	0.0198***	0.0085
	(3.26)	(0.90)
N	9196	9196

t statistics in parentheses
* p<0.1, ** p<0.05, *** p<0.01

From Table 3 and 4 it could be concluded that hypothesis 2 can only be confirmed for the third and fourth lag of the September return, which is insufficient evidence to fully confirm hypothesis 2.

§5.2 Weekday seasonality effect

§5.2.1 The same-weekday return persistence effect

This section examines to what extent there is a same-weekday return persistence effect. According to Table 2 in Appendix A, the mean return on Monday equals -0.0001 while the mean return on Friday equals 0.0009. Therefore, this thesis assumes that the Monday represents a negative mood-day while Friday represents a positive mood-day. This is in line with Hirshleifer et al. (2017). The same-weekday return persistence effect is tested with the following FMB regression:

$$RET_{\text{Mon(Fri)},t} = \eta_{k,t} + \gamma_{k,t} RET_{\text{Mon(Fri)},\text{t}-k} + \varepsilon_t \quad (6)$$

In Table 5 on the next page, the results of regression (6) are presented in column (1). Expected is that the coefficients of the lagged Monday returns are positive and significant. This implies that the return of Monday of previous weeks should have a positive effect on the current Monday return. However, Table 5 column (1) shows that only the second lagged Monday return has a significant effect, but this is only at the 10% level. Keloharju et al. (2016) and Hirshleifer et al. (2017) also find an insignificant coefficient for the first lag, but, however, the other lags of their analysis show statistically significant and positive coefficients. Based on the evidence resulting from regression (6), this thesis has found insufficient evidence to fully confirm the same-weekday return persistence effect for Mondays.

In Table 6 (page 34), column (1), regression results of the same-weekday return persistence effect for Friday are presented. The table shows that 9 lags are insignificant, while the sixth lagged Friday return has a positive and significant effect when an alpha of 10 percent is used. Again, *H3: "The lagged same-day return is positively related to the current same-day return, which implies that relative performance of stocks persists during the same day, week after week."* cannot be confirmed sufficiently based on the results of Table 5 and 6, which conflicts with results of Hirshleifer et al. (2017).

Table 5: The same-weekday return persistence (1) & incongruent-weekday return reversal (2).

	(1) RETmon	(2) RETfri
l1RETmon	0.0010	-0.0139***
	(0.32)	(-4.17)
l2RETmon	0.0241*	-0.0127
	(1.69)	(-1.11)
l3RETmon	-0.0005	0.0132
	(-0.14)	(0.82)
l4RETmon	0.0045	-0.0117
	(1.64)	(-0.78)
l5RETmon	-0.0123	0.0138
	(-1.00)	(0.88)
l6RETmon	-0.0013	-0.0000
	(-0.16)	(-0.01)
l7RETmon	-0.0091	-0.0057
	(-0.99)	(-1.16)
l8RETmon	0.0045	-0.0007
	(1.22)	(-0.17)
l9RETmon	0.0058	-0.0025
	(1.52)	(-0.47)
l10RETmon	0.0097	-0.0033
	(1.17)	(-0.72)
_cons	-0.0000	0.0008***
	(-0.07)	(7.27)
N	790213	790813

t statistics in parentheses
* p<0.1, ** p<0.05, *** p<0.01

§5.2.2 The incongruent-weekday return reversal effect

This paragraph elaborates on the incongruent-weekday return reversal effect. As mentioned in paragraph §5.2.1, assumed is that Monday is the negative-mood day while Friday is the positive-mood day. The incongruent-weekday return reversal effect is tested with the following regression:

$$RET_{\text{Mon(Fri)},t} = \eta_{k,t} + \gamma_{k,t} RET_{\text{Fri(Mon)},\text{t}-k} + \varepsilon_t \qquad (7)$$

According to Hirshleifer et al. (2017), one should expect that the lagged return of Monday has a negative effect on the current Friday return, while the lagged return of Friday should have a negative effect on the current Monday return. In Table 5 column (2) and in Table 6 column (2) the regression coefficients are presented. Table 5 column (2) shows that the first lagged return of Monday has a negative effect on the current return of Friday and the effect is significant at the 1% level. The other coefficients of the 9 lagged Monday return variables are negative except of the third and fifth lagged variables, but their influence on the current Friday return

is insignificant. For the first lag, the incongruent-weekday return reversal effect could be confirmed. The negative effect implies that when the Monday return is higher, the following Friday return is lower and vice versa. However, for the other 9 lags there is no significant return reversal effect. Therefore this thesis concludes that there is insufficient evidence of an incongruent-weekday return reversal effect when the current Friday return is regressed against the lagged Monday returns. It is worth mentioning that the first lagged Monday return represents the Monday return in the same week of the current Friday return.

Subsequently, when the current Monday return is regressed against the lagged Friday returns, it turns out that the first lagged Friday return has a positive, significant effect on the current Monday return with an alpha of 1%. This implies that when the Friday return is higher, the following Monday return is higher and vice versa. More specifically, when the first lagged Monday return is one standard deviation higher than the mean, the resulting increase in the following Friday return equals 1.71% multiplied by the standard deviation. The regression results are presented in Table 6, column (2) on the next page. From the regression results it could be concluded that there is no incongruent-weekday return reversal effect. Instead, the only significant coefficient of the lagged Friday return is positive, which is in contrast with what would be expected based on Hirshleifer et al (2017). This implies that returns on Friday have a positive effect on the returns of the next Monday. On possible reason for this could be that stock prices on average follow trends, which implies that in some periods on average stock prices increase while in other periods stock prices decrease. More specifically, this would suggest that when the Friday return is positive, the trend is followed up and observable in the Monday return. However, based on Table 5 column (2) and Table 6 column (2) it could be concluded that there is insufficient evidence to confirm the associated hypothesis *H4: "A cross-sectional return reversal effect takes place across two days with expected incongruent mood-states for at least a few weeks. This implies that the lagged incongruent-mood day returns are negatively related to the incongruent-day return."*

Table 6: The same-weekday return persistence (1) & incongruent-weekday return reversal (2).

	(1) RETfri	(2) RETmon
l1RETfri	-0.0044	0.0171***
	(-0.85)	(4.92)
l2RETfri	-0.0044	-0.0064
	(-0.49)	(-1.32)
l3RETfri	-0.0013	0.0024
	(-0.39)	(0.65)
l4RETfri	0.0053	-0.0044
	(1.16)	(-1.32)
l5RETfri	0.0016	0.0064
	(0.29)	(1.30)
l6RETfri	0.0079*	0.0115
	(1.71)	(1.11)
l7RETfri	0.0073	-0.0048
	(0.82)	(-1.03)
l8RETfri	0.0027	-0.0030
	(0.32)	(-0.81)
l9RETfri	-0.0033	-0.0042
	(-0.67)	(-0.65)
l10RETfri	0.0038	-0.0034
	(0.66)	(-0.76)
_cons	0.0008***	-0.0001
	(7.03)	(-0.58)
N	790722	790722

t statistics in parentheses
* p<0.1, ** p<0.05, *** p<0.01

§5.3 Mood Beta and Return Seasonality

§5.3.1 Mood beta and calendar month seasonal effect

In this section the calendar month seasonal returns are forecasted by using mood beta. This is done in two stages, using the method of Hirshleifer et al. (2017). In the first stage, mood beta is estimated for each stock by performing rolling regressions of a stock's January and September excess return on the aggregate market excess return, using a 10-year rolling window. The mood beta coefficient which is estimated using this method measures the average stock return response to changes in the aggregate market excess return in January and September, the months in which is assumed that mood swings dictate systematic return variation. Basically, a stock tends to earn higher January return and lower September return when mood beta is higher, so mood beta is a proxy for a stock's sensitivity to mood. In order to be clear, January and September excess returns are retrieved by subtracting the risk-free

rate from the raw returns, which is more specifically explained in paragraph §4.1. The aggregate market return is assumed to be the Morgan Stanley Capital International index of Europe (MSCI Europe) and the excess aggregate market return is the raw MSCI return minus the risk-free rate. The first stage regression looks like follows:

$$XRET_{i,Jan(Sep)=}\alpha_i + \beta^{Mood}_{i,Jan(Sep)}XRET_{A,Jan(Sep)} + \varepsilon_i \quad (8)$$

In the second stage the mood betas of the first stage are being tested whether they are significant, by running Fama-MacBeth regressions of stocks' January and September returns on their own lagged mood betas (10 lags). The regressions look as follows:

$$RET_{Jan,t} = \eta_{k,t} + \lambda_{k,t}\beta^{Mood}_{Jan,t-k} + \varepsilon_t \quad (9)$$

$$RET_{Sep,t} = \eta_{k,t} + \lambda_{k,t}\beta^{Mood}_{Sep,t-k} + \varepsilon_t \quad (10)$$

λ_k is the average slope coefficient and thereby called the mood premium. The mood premium coefficient captures the size of the return spread between the high and low mood beta stocks in positive or negative mood seasons. In Table 7 on the next page the regression results of regression (9) are presented. The table shows that the estimated mood beta premiums are both positive and negative, while only positive coefficients are expected. However, the coefficients are of all 10 lags are statistically insignificant. Only the error term has a positive and significant coefficient at the 1% level, but this variable has less importance compared to the 10 annual lags. Subsequently, when looking to Table 8 on the next page, it could be seen that in line with Table 7 all 10 lags are insignificant. Thereby this thesis is unable to support the theory that return seasonality is related to stocks' sensitivity to mood when measuring at the monthly level.

Table 7: Mood beta and return seasonality - January -.

	(1) RETjan
l1BMOODjan	-0.0107
	(-0.76)
l2BMOODjan	0.0112
	(0.74)
l3BMOODjan	0.0030
	(0.25)
l4BMOODjan	-0.0107
	(-0.85)
l5BMOODjan	0.0201
	(1.28)
l6BMOODjan	-0.0078
	(-0.59)
l7BMOODjan	-0.0059
	(-0.65)
l8BMOODjan	-0.0039
	(-0.36)
l9BMOODjan	0.0059
	(0.44)
l10BMOODjan	0.0027
	(0.25)
_cons	0.0361***
	(5.17)
N	9964

t statistics in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Table 8: Mood beta and return seasonality - September -.

	(1) RETsep
l1BMOODsep	-0.0254
	(-1.68)
l2BMOODsep	0.0132
	(0.96)
l3BMOODsep	-0.0107
	(-0.92)
l4BMOODsep	0.0047
	(0.43)
l5BMOODsep	0.0020
	(0.15)
l6BMOODsep	0.0026
	(0.26)
l7BMOODsep	0.0132
	(1.14)
l8BMOODsep	-0.0166
	(-1.39)
l9BMOODsep	0.0154
	(0.82)
l10BMOODsep	-0.0117
	(-0.77)
_cons	-0.0001
	(-0.01)
N	9708

t statistics in parentheses
* p<0.1, ** p<0.05, *** p<0.01

§5.3.2 Mood beta and weekday seasonal effect

In this section the relation between weekday seasonality return effects and mood beta will be examined. This is done according to the same steps which are used in paragraph §5.3.1. In the first step, the mood betas are estimated according to the following regression using a 6-month rolling window:

$$XRET_{i,Mon(Fri)=} \alpha_i + \beta^{Mood}_{i,Mon(Fri)} XRET_{A,Mon(Fri)} + \varepsilon_i \qquad (11)$$

In the second step, the mood beta coefficients resulting from regression (11) are used in order to test whether they could explain the return on Mondays and Fridays. This is done according to regression (9) and (10) but then with daily returns instead of returns at the monthly level. It is expected that the coefficients are positive and significant and thus in line with the results of Hirshleifer et al. (2017).

Table 9: Mood beta and return seasonality - Monday -.

	(1) RETmon
l1BMOODmon	0.0010
	(0.93)
l2BMOODmon	-0.0016
	(-1.11)
l3BMOODmon	0.0004
	(0.29)
l4BMOODmon	-0.0005
	(-0.30)
l5BMOODmon	0.0010
	(0.66)
l6BMOODmon	-0.0000
	(-0.03)
l7BMOODmon	-0.0004
	(-0.33)
l8BMOODmon	0.0002
	(0.14)
l9BMOODmon	0.0004
	(0.20)
l10BMOODmon	-0.0005
	(-0.58)
_cons	-0.0001
	(-1.05)
N	762320

t statistics in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Table 10: Mood beta and return seasonality - Friday -.

	(1) RETfri
l1BMOODfri	0.0021**
	(2.15)
l2BMOODfri	-0.0015
	(-1.28)
l3BMOODfri	0.0003
	(0.24)
l4BMOODfri	-0.0013
	(-1.13)
l5BMOODfri	0.0010
	(0.82)
l6BMOODfri	-0.0004
	(-0.37)
l7BMOODfri	0.0005
	(0.54)
l8BMOODfri	-0.0014
	(-1.38)
l9BMOODfri	0.0001
	(0.06)
l10BMOODfri	0.0007
	(0.94)
_cons	0.0010***
	(16.51)
N	762766

t statistics in parentheses
* p<0.1, ** p<0.05, *** p<0.01

The regression results are shown in Table 9 and 10 above. In line with the regression results at the monthly level, the coefficients are almost all insignificant. Only the first lag of mood beta has a positive and significant effect on the return of Friday, which is in line with Hirshleifer et al. (2017). Nonetheless, this implies that this thesis is not able to find evidence supporting the theory of Hirshleifer et al. (2017) that return seasonality is related to stocks' sensitivity to mood when measuring at a daily basis. This means that *H5: "Mood beta is a positive predictor of the cross-section of stock returns during positive mood states and a negative predictor during negative mood states."* is rejected.

§5.4 The influence of soccer results on stock returns

Now this thesis has already tested whether there is return persistence and reversal and whether mood beta is a proxy for stocks' sensitivity to mood, the influence soccer results on

stock prices should be examined. Ultimately, the main goal of this thesis is to check whether mood beta really measures a stocks' sensitivity to mood. This is done by checking whether there is correlation between a stocks' unique mood beta and between the stock return response after soccer wins and losses. First, the influence of soccer results on stock returns will be examined in this paragraph. Subsequently, paragraph §5.5 links the mood betas to return responses due to soccer wins and losses.

In order to test what is the influence of soccer wins and losses on stock returns, the method described in the research method paragraph §4.2 is applied which is a method derived from Edmans et al. (2007). To be clear, the null hypothesis is that stock markets are unaffected by the outcomes of soccer matches. On the other hand, hypothesis 6 is that the effect of a national team win on the stock return of companies in that corresponding country is positive, while the effect of a loss is negative. The results of regression (2) of paragraph §4.2, in which the residuals (abnormal returns) are regressed against dummy variables for wins and losses, are shown in Table 8 below. Column (1) includes all games, for column (2) the regression is run only for group games and column (3) only includes elimination games. The standard errors are clustered, which allows for intragroup correlation. These clustered standard errors are appropriate, since there are repeated soccer results observations for each country. This is the reason the usual requirement that observations are independent cannot be met.

Table 8: The soccer anamoly by type of game.

	(1) All games	(2) Group games	(3) Elimination games
Day after Win	-0.0517	-0.0072	-0.1816
	(-1.49)	(-0.33)	(-1.67)
Day after Loss	-0.0803**	-0.0770	-0.0858**
	(-2.24)	(-1.46)	(-2.68)
Constant	0.0002**	0.0002**	0.0003*
	(2.38)	(2.38)	(2.09)
Observations	1333388	1331869	1328401

t statistics in parentheses
* p<0.1, ** p<0.05, *** p<0.01

From Table 8 it could be seen that there is a negative effect of soccer wins on the next day stock return. However, the win coefficients are insignificant which makes them irrelevant. It is more interesting to see that there is indeed a negative, statistically significant effect of

soccer losses on stock returns. The coefficient for the loss dummy is significant at the 5% level. More specifically, when all games are included in the sample, a soccer loss causes the abnormal return to be 8 basis points lower than the abnormal return would have been without the loss.

Recall hypothesis 6: *H6: "International soccer results do have an influence on stock returns through moods and emotions. More specifically, soccer wins lead to a positive stock market reaction while losses lead to a negative reaction."* From Table 8 could be concluded that the claim that stock returns are unaffected by soccer results can be rejected. Instead, Table 8 provides evidence that is in line with hypothesis 6, since the loss effect is significant and negative. The win effect is also negative, but insignificant so irrelevant. However, the loss coefficient of Edmans et al. (2007) is stronger (-0.212). One logical reason for this bigger coefficient is that Edmans et al. simply have more win and loss events in their sample, since they use soccer results of 44 countries while this thesis only uses soccer results of the 17 European countries presented in paragraph §4.1. However, despite of the lower number of event, international soccer results do have an influence on stock returns and hypothesis 6 could at least partially be confirmed.

Consequently, the coefficients in Table 8 show that the loss effect is stronger when game importance increases. This could be illustrated by Table 8, column (2) and (3). Column (2) shows that there even is no significant win or loss effect when only group games are taken into account, while the loss dummy coefficient is stronger when only elimination games are included. Edmans et al. (2007) argue that it seems natural that elimination games in later stages of competitions have the strongest mood effect, since such games have more media attention because each single loss could send a national team home. On the other hand, it could be that some group games are not directly relevant anymore when a team already has too few points to reach the knock-out stage. Therefore, this thesis additionally tests whether the soccer anomaly significantly differs between game types for robustness. This is done by adding interaction terms for game type, which is already elaborated specifically in paragraph §4.2. The results of this test are shown in Table 9 column (4), however, the interaction variables are insignificant. Therefore *H8: "The soccer anomaly is stronger for elimination games."* is rejected.

Moreover, an additional interaction term is added, which tests the extent whether a country is a soccer country or not. The coefficients for this term are presented in Table 9, column (3). A country is defined as a soccer country when soccer is the most popular sport in that country. The sport popularity is measured by National Geographic, by examining what sports is the most watched sports on television. Appendix B, Graph 5 shows the most popular sport for each country.

It could be concluded that it matters whether a country is a soccer country; the main effects slightly change, while the interaction term {Win * SoccerCountry} is positive and significant at the 1% level. This evidence implies that the positive return response after a soccer win increases when a country is a soccer country. However, the main coefficient for wins is still not significant, while the main coefficient for losses is still significant at the 5% level but slightly less negative. Overall, *H9: "The soccer anomaly is stronger for soccer countries."* is partially confirmed. The stock return response after soccer wins is more positive if a country is a soccer country. However, the stock return response after losses is not stronger for soccer countries.

§5.5 The relation between mood beta and the soccer anomaly

Now the soccer betas and the mood betas are estimated, the major contribution of this thesis is addressed. In paragraph §5.3 is tested whether mood beta is indeed a measure for a stocks' sensitivity to mood, like Hirshleifer et al. (2017) claim. However, this thesis found results which are not in line with Hirshleifer et al., since the coefficients of mood beta were statistically insignificant. However, the major goal of this thesis is to check whether the mood betas are correlated with the soccer betas, and thus are indeed a predictor of a stocks' sensitivity to mood. The insignificance of the mood betas decreases the chance to find significant correlation between a stocks' mood beta and a stocks' response to a soccer win or loss. Although the chance to find significant correlation is decreased by the insignificance of the mood betas, it is promising to observe that differences in return response to soccer wins and losses exist. The coefficients for wins and losses are presented in Graph 3 and 4 in Appendix B. These graphs show that the stock return responses are pretty much normally divided, but, however, there are big differences between companies in return responses to soccer results.

This thesis now will test whether the differences in return responses could be linked to sensitivity to mood. In other words, this thesis will test whether there could be found correlation between the soccer win and loss coefficients and the mood betas. However, it would still be surprising if this thesis is able to find correlation between the mood betas and the soccer results effects, due to the fact that this thesis' mood betas have shown to be insignificant. Nonetheless, this thesis still performs regression (3) described in paragraph §4.2 in order to find correlation between mood beta and the soccer anomaly, by adding the mood betas as interaction variables like is shown in regression (3). If the interaction variables are significant, it could be concluded that the mood betas are indeed a measure of a stocks' sensitivity to mood since the soccer effects and the mood betas are correlated.

Recall, regression (3) looks as follows:

$$\varepsilon_{i,t} = \beta_0 + \beta_{Win} W_{i,t} + \beta_{Loss} L_{i,t} + \{\beta_i^{Win} * \beta_i^{Mood}\} + \{\beta_i^{Loss} * \beta_i^{Mood}\} + \varepsilon_{i,t} \quad (3)$$

In Table 9 below, the regression results of regression (3) are shown.

Table 9: The influence of Mood Beta (+ Soccer Country and Game Type for robustness) on the soccer anamoly

	(1) Baseline	(2) + Mood Beta	(3) + Soccer Country	(4) + Type of Game	(5) All
Day after Win	-0.0517	-0.0518	-0.0542	0.0625	0.0599
	(-1.49)	(-1.48)	(-1.58)	(0.94)	(0.90)
Day after Loss	-0.0803**	-0.0804**	-0.0794**	-0.0200	-0.0199
	(-2.24)	(-2.24)	(-2.25)	(-0.30)	(-0.30)
β-Win x Mood Beta		-0.0090			-0.0090
		(-1.62)			(-1.63)
β-Loss x Mood Beta		-0.0066			-0.0066
		(-1.66)			(-1.66)
Win_SoccerCountry			0.0189***		0.0242***
			(3.77)		(6.77)
Loss_SoccerCountry			-0.0099		-0.0064
			(-0.52)		(-0.33)
Win_type				-0.0786	-0.0790
				(-1.34)	(-1.35)
Loss_type				-0.0347	-0.0345
				(-1.56)	(-1.54)
Constant	0.0002**	-0.0004	0.0002**	0.0002**	-0.0004
	(2.38)	(-1.49)	(2.38)	(2.38)	(-1.49)
Observations	1333388	1333388	1333388	1333388	1333388

t statistics in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Theoretically, expected is that the interaction variables of the mood betas are statistically significant. More specifically, the interaction variable $\{\beta_i^{Win} * \beta_i^{Mood}\}$ is expected to be

positive, which implies that the higher the mood beta of a stock is, the higher is the coefficient for a soccer win. On the other hand, in theory the term $\{\beta_i^{Loss} * \beta_i^{Mood}\}$ is expected to be negative, which implies that the higher the mood beta, the more negative is the coefficient of a soccer loss. This would mean that the higher the mood beta, the stronger the mood effects of soccer wins and losses.

Table 9 column (1) shows the baseline win and loss coefficients without interaction effects, resulting from regression (2). Subsequently, column (2) shows the results of regression (3) in which the interaction variables for mood beta are included. The coefficient of the mood beta interacting with soccer wins is negative, which is not in line with what is expected. However, this coefficient is not significant. Meanwhile, the coefficient of the mood beta interacting with soccer losses is also negative, which is in line with what would have been expected. This implies that the higher the mood beta, the lower the coefficient for soccer losses, the bigger the negative response of stock returns to soccer losses. However, this coefficient also is not significant, although the t-value is 1.66. This implies that when an alpha of 15% is used, the coefficient is significant. However, an alpha of 15% is rarely used in statistics. Therefore it could be concluded that there is no significant interaction between a stocks' mood beta and the return response to soccer results. Recall, hypothesis 7 is as follows:

H7: There is a positive correlation between the mood betas and the coefficients for soccer wins, and a negative correlation between the mood betas and the coefficients for soccer losses.

Based on Table 9, it could be concluded that hypothesis 7 is rejected. There is interaction between mood beta and the soccer results effects, however, this interaction is not statistically significant. However, with a t-value of 1.66 and a negative coefficient for the loss interaction term, the interaction seems promising for further research. This thesis suggests other economists to either improve the mood beta analysis of this thesis, or to use a different stock data sample in order to find significant mood betas. By doing so, economists could really test whether mood betas indeed measure stocks' sensitivity to mood when is controlled for soccer results as a mood-influencing factor. Unfortunately, soccer is not the most popular sport in the U.S. Therefore the analysis of this thesis of the link of mood betas with soccer betas could not be investigated using the sample of Hirshleifer et al. (2017) including only U.S. stocks.

6. Conclusion

This thesis has combined the approaches of two articles; the article of Hirshleifer et. al (2017) and the article of Edmans et al. (2007). This thesis tested whether there is a return persistence effect, whether there is a return reversal effect and whether a stocks' unique mood beta could explain the stocks' sensitivity to mood. Hirshleifer et al. (2017) uses a sample including only U.S. stocks, but this thesis includes only European stocks from the STOXX Europe 600. The main research question of this thesis is:

"Does the mood beta concept of Hirshleifer, Jiang and Meng (2017) deliver mood betas which really reflect stocks' sensitivity to mood when controlling for soccer results effects?"

Hirshleifer et al. (2017) found that relative performance of stocks tends to persist in future periods with positive mood, in which January and Friday returns represent returns in periods with positive mood. This thesis tested whether there is a return reversal effect, however, it could be concluded that only some lagged returns have a positive and significant effect on the current return. This implies that the evidence found for a return persistence effect is not as strong as the evidence of Hirshleifer et al. (2017).

Relative performance also tends to reverse in periods with negative mood (Mondays, September, October) which is called return reversal. This thesis has tested whether there is a return reversal effect, and concludes that there is insufficient evidence to confirm the hypothesis that there is a return reversal effect across incongruent-mood period returns.

Since Hirshleifer et al. (2017) has found significant return persistence and reversal effects, they argue that stocks react to mood in a proportional way, and that there could be differences in sensitivity to mood between stocks. However, this thesis is not able to find sufficient evidence for the return persistence and reversal effect. Still, the hypothesis that each stock has a unique sensitivity to mood is tested. Conceptually, stocks with higher mood betas earn higher expected returns during positive mood periods, but lower returns during negative mood seasons which implies that high mood beta stocks are more sensitive to mood compared to low mood beta stocks. However, this thesis was not able to find evidence supporting the theory return seasonality is related to stocks' sensitivity to mood. This means that the hypothesis that mood beta is a positive predictor of the cross-section of stock returns during positive mood states and a negative predictor during negative mood states is rejected.

Hereafter, the estimated mood betas are used in order to find correlation between the effect of international soccer wins and losses and the estimated stocks' sensitivity to mood, i.e. the mood beta. However, this thesis found results which are not in line with Hirshleifer et al. since the coefficients of mood beta were statistically insignificant. The insignificance of the mood betas decreases the chance to find significant correlation between a stocks' mood beta and a stocks' response to a soccer win or loss. However, there is a difference in stock return response after soccer wins and returns observable, which could be explained by mood betas.

First, it is investigated whether soccer results have a significant influence on stock returns. This thesis finds evidence that is in line with the hypothesis that international soccer results have an influence on stock returns. More specifically, the results show that soccer losses lead to a significant, negative stock return response. However, the effect of soccer wins is insignificant, which is in line with existing literature about the soccer anomaly.

Second, this thesis tested whether there is correlation between the mood betas and the stock market responses after international soccer wins and losses. If the claim of Hirshleifer et al. (2017) is valid, the interaction term of mood beta and soccer wins should have a positive effect, while the term of mood beta and soccer losses should have a negative effect. This thesis concludes that there is interaction between mood beta and the soccer results effects, however, this interaction is not statistically significant. To provide an answer to the main research question of this thesis; this thesis has not found significant mood betas which really reflect stocks' sensitivity to mood by using the approach of Hirshleifer et al. (2017). This thesis suggests other economists to either improve the mood beta analysis of this thesis, or to use a different stock data sample in order to find significant mood betas. By doing so, economists could really test whether mood betas indeed measure stocks' sensitivity to mood when is controlled for soccer results as a mood-influencing factor.

7. Discussion

This section examines the possible flaws and limitations of this thesis. Overall, the major concern of this thesis is that the mood betas have shown to be insignificant. This implies that this thesis has not estimated a significant beta for each stock, which captures the sensitivity of a security to mood. Therefore the chance to find correlation with other mood-influencing variables like soccer wins and losses could not be examined properly, which makes conclusions about the correlation between mood beta and soccer betas less valid. The main cause of the lack of significance of the mood betas is that this thesis also finds contrary results regarding the return persistence effect and the return reversal effect. It seems logical that therefore the mood betas are not able to significantly measure stocks´ sensitivity to mood. Although the method used in this thesis is not completely the same as the method of Hirshleifer et al. (2017) this thesis' results show that at least Hirshleifer et al. (2017) could be questioned and that further research regarding mood betas is appropriate.

Another possible flaw of this thesis could be that this thesis uses the German 3-year bond yield for the risk-free rate in order to compute abnormal returns. This assumption is built on two reasons, which are explained in detail in paragraph §4.1. However, this assumption has an impact on the resulting abnormal returns, which could eventually affect the significance of the mood betas. However, Hirshleifer et al. (2017) did not specify what they used as risk-free rate. This thesis needed an European risk-free rate since only European stocks were included, and the German 3-year bond yield seemed to be the best choice.

Subsequently, this thesis has investigated the influence of soccer results on stock returns. Soccer results are assumed to influence stock returns through moods and emotions. However, the influence could be explained by other factors, for example by company sales. Intuitively, companies' sales increase after a soccer win while companies' sales decrease after a soccer loss when companies operate in the catering industry. However, the effect of sales is not observable directly after soccer results, while the stock market return is directly observable. Since this thesis uses soccer results events while measuring only the day-after stock return response, the effect of company sales is not relevant at this short-time horizon.

Moreover, this thesis investigates the effect of soccer results of the national team on companies' stock return of that specific country. However, when these companies are well

diversified, there could be a stock return response in that specific country, but also in other countries and these responses could be contrary. This implies that the stock return responses to soccer results could cancel each other out when companies are present in multiple countries. To illustrate; there could be a decrease in stock return of Royal Dutch Shell after the Dutch team lost a game against Germany. However, since Shell also operates in Germany, the return response of Germanies' win on Shell's stock could be positive. However, this thesis still finds significant responses after soccer results so the argument above seems to have no impact.

Subsequently, it could be argued that the coefficients of Edmans et al. (2007) are stronger. However, this could be logically explained by the fact that they use more soccer events. This thesis only uses soccer evens of 17 countries, while Edmans et al. (2007) use results of 44 countries. On top of that, in order to increase the number of events Edmans et al. even conducted their research by using cricket, rugby, ice hockey and basketball matches.

Finally, the effect of matches played during weekends is measured by the stock return response of the next trading day. This is a potential asynchrony, since part of the reaction may have been incorporated in prices before the measurement day, while this has not been observable because the market was closed. Also the effect could have been influenced by other games played in the weekend. These arguments could weaken the significance of the soccer anomaly. However, the results still show to be significant.

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9. Appendix

Appendix A – Summary statistics

Table 1: Summary statistics - Monthly

variable	N	mean	sd	min	max
time	319800	267	153.8638	1	533
companyid	319800	300.5	173.2051	1	600
RETjan	14998	.0256246	.1232811	-.5870445	5.545551
RETsep	14715	-.0132248	.1026941	-.8191304	1.018347
REToct	14735	.0125751	.1081343	-.795501	1.060246
date	533	12844.3	4687.625	4749	20940
RETmsci	319800	.0062871	.0508848	-.2131826	.2309246
rfrate	319800	.0484164	.032241	-.0093	.1137
XRETjan	14998	-.00777	.1231127	-.6008345	5.459551
XRETsep	14715	-.0481792	.1105474	-.8521004	.9683871
XREToct	14735	-.0222244	.1142141	-.819531	.9812989
XRETmsci	319800	-.0421292	.0614738	-.2554757	.1379246
lag1RETjan	14399	.026493	.1250156	-.5870445	5.545551
lag2RETjan	13808	.0300682	.1254121	-.5870445	5.545551
lag3RETjan	13228	.0291176	.1268842	-.5870445	5.545551
lag4RETjan	12666	.0311042	.1285877	-.5870445	5.545551
lag5RETjan	12118	.0295745	.1299024	-.5870445	5.545551
lag6RETjan	11573	.027067	.1305515	-.5870445	5.545551
lag7RETjan	11033	.0275886	.132705	-.5870445	5.545551
lag8RETjan	10502	.0288206	.1348814	-.5870445	5.545551
lag9RETjan	9974	.0336397	.1326244	-.4893855	5.545551
lag10RETjan	9450	.0401353	.1316771	-.4893855	5.545551
lag1RETsep	14120	-.0141992	.1039506	-.8191304	1.018347
lag2RETsep	13536	-.0141999	.1050379	-.8191304	1.018347
lag3RETsep	12959	-.0138695	.106578	-.8191304	1.018347
lag4RETsep	12403	-.0160834	.1073371	-.8191304	1.018347
lag5RETsep	11857	-.0184611	.1081527	-.8191304	1.018347
lag6RETsep	11313	-.0157668	.1083896	-.8191304	1.018347
lag7RETsep	10775	-.018854	.1089728	-.8191304	1.018347
lag8RETsep	10246	-.0226691	.1089486	-.8191304	1.018347
lag9RETsep	9718	-.0169111	.105853	-.8191304	1.018347
lag10RETsep	9196	-.018022	.1071173	-.8191304	1.018347
lag1RETOct	14138	.0136777	.1092501	-.795501	1.060246
lag2RETOct	13553	.010913	.1094661	-.795501	1.060246
lag3RETOct	12975	.0112654	.1110264	-.795501	1.060246
lag4RETOct	12418	.0100724	.1124511	-.795501	1.060246
lag5RETOct	11872	.009989	.1141725	-.795501	1.060246
lag6RETOct	11328	.0080173	.1153293	-.795501	1.060246
lag7RETOct	10790	.006293	.1169066	-.795501	1.060246
lag8RETOct	10260	.0071104	.1184736	-.795501	1.060246
lag9RETOct	9732	.0161705	.1098024	-.6182315	1.060246
lag10RETOct	9210	.0163054	.1113473	-.6182315	1.060246

Table 2: Summary statistics - Daily

variable	N	mean	sd	min	max
time	8190600	6826	3940.704	1	13651
companyid	8190600	300.5	173.2049	1	600
Date	8190600	11382.8	5516.986	1827	20937
RETmsci	7095000	.000289	.0108789	-.0967741	.1129126
rfrate	8190600	.0525548	.0311202	-.00992	.1143
RETmon	796213	-.0001176	.0213444	-.8330733	1.391509
RETtue	796402	.000499	.0220745	-.7757285	4.843338
RETwed	796494	.0007586	.0214931	-.6420321	1.419437
RETthu	796585	.0006888	.0212728	-.7222739	.8230769
RETfri	796722	.0009048	.0204758	-.6206896	1.28631
XRETmon	796213	-.0357811	.0377119	-.8649433	1.394939
XRETfri	796722	-.0347143	.0369518	-.6683396	1.20591
l1RETmon	795613	-.0001357	.0213358	-.8330733	1.391509
l2RETmon	795013	-.0001358	.0213439	-.8330733	1.391509
l3RETmon	794413	-.0001366	.0213498	-.8330733	1.391509
l4RETmon	793813	-.0001336	.0213533	-.8330733	1.391509
l5RETmon	793213	-.0001305	.0213591	-.8330733	1.391509
l6RETmon	792613	-.0001306	.0213658	-.8330733	1.391509
l7RETmon	792013	-.0001329	.0213714	-.8330733	1.391509
l8RETmon	791413	-.0001315	.0213775	-.8330733	1.391509
l9RETmon	790813	-.0001334	.0213832	-.8330733	1.391509
l10RETmon	790213	-.0001355	.0213892	-.8330733	1.391509
l1RETfri	796122	.0009061	.0204795	-.6206896	1.28631
l2RETfri	795522	.000908	.0204851	-.6206896	1.28631
l3RETfri	794922	.0009087	.0204928	-.6206896	1.28631
l4RETfri	794322	.0009076	.0204979	-.6206896	1.28631
l5RETfri	793722	.0009063	.0205023	-.6206896	1.28631
l6RETfri	793122	.0009068	.020508	-.6206896	1.28631
l7RETfri	792522	.0009056	.0205128	-.6206896	1.28631
l8RETfri	791922	.0009041	.0205179	-.6206896	1.28631
l9RETfri	791322	.0009057	.0205229	-.6206896	1.28631
l10RETfri	790722	.0009123	.0205264	-.6206896	1.28631

Table 3: Summary statistics - The Soccer Anomaly

variable	N	mean	sd	min	max
date	3349271	15203.46	2747.447	10230	19926
companyid	3349271	298.3018	176.9972	1	600
country	3349271	21.31404	11.21328	3	41
return	2300931	.0006795	.0606935	-8.325165	9.291142
twin	3349271	.0034969	.059031	0	1
ttie	3349271	.0014657	.0382563	0	1
tloss	3349271	.0022918	.0478183	0	1
type	3349271	.011779	.1668359	0	6
mon	3349271	.1930504	.3946922	0	1
tue	3349271	.2029627	.402205	0	1
wed	3349271	.2032884	.4024454	0	1
thu	3349271	.2016672	.401245	0	1
ph1	3349271	.0202925	.1409989	0	1
ph2	3349271	.0276233	.1638911	0	1
ph3	3349271	.0279971	.1649646	0	1
ph4	3349271	.0202265	.1407742	0	1
ph5	3349271	.006932	.0829693	0	1
marketreturn	3349271	.0003843	.0437611	-6.436695	8.523635
SoccerCountry	3349271	.9790957	.1430639	0	1
returnlag	1810953	.0005004	.0614051	-7.738054	9.291142
marketreturnlag	2634212	.0003116	.0445601	-6.436696	8.523636
marketreturnlead	2634212	.000448	.0418541	-6.436696	6.476375
convar	3349271	.0020049	.0421897	.0001199	19.86129
consd	3349271	.0316413	.031682	.010951	4.456601
conreturn	2300931	.0258842	1.161554	-110.8749	133.1284
conreturnstd	2300931	-2.51e-11	.999997	-88.18013	107.477
conreturnstdlag	2300437	-.0000946	.9996892	-88.18013	107.477
UniqueMoodBeta	3342559	.7459922	.2375829	.1047214	1.721769
xtwinxMoodBeta	3212647	-.0356374	.3158006	-1.374102	2.264423
xtlossxMoodBeta	3212647	-.0433875	.3135777	-1.107132	1.742811
yhat	1333388	-.0036327	.4015807	-32.78865	32.34215
residuals	1333388	-3.03e-11	.8936468	-53.11255	106.0795
stdSoccerCountry	3349271	-4.00e-09	1	-6.843767	.1461183
Win_SoccerCountry	3349271	.0004817	.0164353	-6.843767	.1461183
Loss_SoccerCountry	3349271	.0002034	.0304877	-6.843767	.1461183
Win_type	3349271	.005944	.120979	0	6
Loss_type	3349271	.0043693	.1087057	0	6
xtwin	3212647	-.0540914	.3986127	-3.432902	2.49991
xtloss	3212647	-.0600312	.351617	-1.327185	2.166913

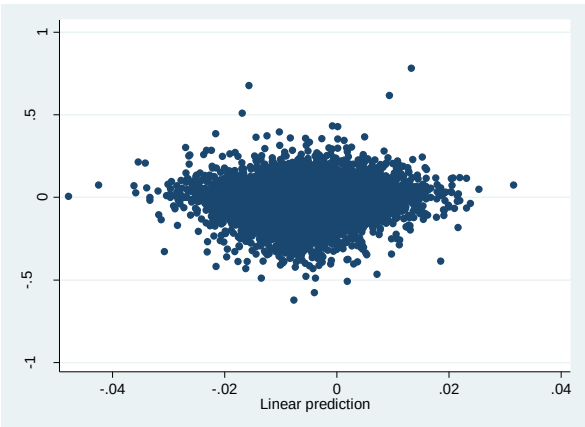
Appendix B – Regression results

Table 1: The same-month return persistence effect for January.

	(1) OLS	(2) GLS	(3) FE	(4) FMB
lag1RETjan	0.0712***	0.0712***	0.0229**	0.0544**
	(7.02)	(7.02)	(2.20)	(2.38)
lag2RETjan	0.0044	0.0044	-0.0410***	0.0220
	(0.44)	(0.44)	(-3.93)	(0.98)
lag3RETjan	-0.0341***	-0.0341***	-0.0771***	0.0163
	(-3.38)	(-3.38)	(-7.42)	(0.84)
lag4RETjan	-0.0878***	-0.0878***	-0.1320***	-0.0129
	(-8.87)	(-8.87)	(-12.88)	(-0.61)
lag5RETjan	0.0641***	0.0641***	0.0217**	0.0251*
	(6.48)	(6.48)	(2.12)	(1.76)
lag6RETjan	0.0224**	0.0224**	-0.0131	0.0120
	(2.28)	(2.28)	(-1.29)	(0.70)
lag7RETjan	0.0471***	0.0471***	0.0156	0.0393**
	(4.92)	(4.92)	(1.58)	(2.22)
lag8RETjan	0.0510***	0.0510***	0.0281***	-0.0139
	(5.89)	(5.89)	(3.15)	(-0.90)
lag9RETjan	0.0626***	0.0626***	0.0438***	0.0136
	(7.28)	(7.28)	(4.94)	(1.19)
lag10RETjan	0.0027	0.0027	-0.0113	0.0161
	(0.35)	(0.35)	(-1.43)	(1.01)
_cons	0.0109***	0.0109***	0.0188***	0.0167**
	(9.18)	(9.18)	(14.64)	(2.18)
N	9450	9450	9450	9450

t statistics in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Graph 1: RETsep



Graph 2: RETsep after removing I.O.

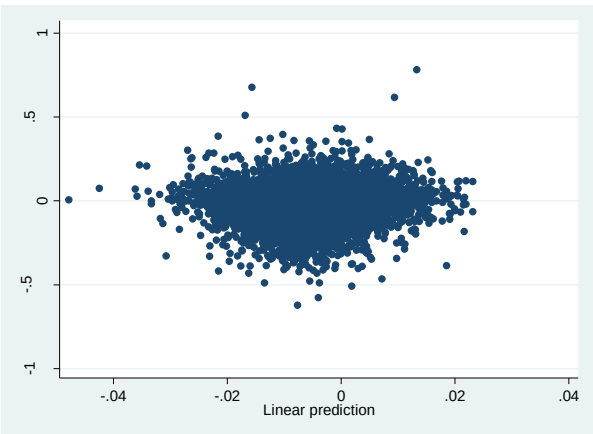


Table 2: The same-month return persistence effect for September.

	(1) OLS	(2) GLS	(3) FE	(4) FMB
lag1RETsep	0.0557***	0.0557***	0.0016	0.0251
	(5.41)	(5.41)	(0.15)	(0.90)
lag2RETsep	-0.1250***	-0.1250***	-0.1743***	-0.0271
	(-12.39)	(-12.39)	(-16.75)	(-1.40)
lag3RETsep	0.0671***	0.0671***	0.0151	-0.0112
	(6.74)	(6.74)	(1.47)	(-0.61)
lag4RETsep	-0.0453***	-0.0453***	-0.0910***	-0.0324**
	(-4.62)	(-4.62)	(-8.93)	(-2.44)
lag5RETsep	-0.0197**	-0.0197**	-0.0644***	0.0415***
	(-2.04)	(-2.04)	(-6.38)	(3.13)
lag6RETsep	0.0033	0.0033	-0.0374***	-0.0233
	(0.34)	(0.34)	(-3.75)	(-1.40)
lag7RETsep	0.0227**	0.0227**	-0.0162	0.0197
	(2.39)	(2.39)	(-1.64)	(1.07)
lag8RETsep	-0.0103	-0.0103	-0.0423***	0.0161
	(-1.09)	(-1.09)	(-4.32)	(0.88)
lag9RETsep	0.0525***	0.0525***	0.0255***	0.0121
	(5.46)	(5.46)	(2.58)	(0.79)
lag10RETsep	0.0323***	0.0323***	0.0091	0.0070
	(3.43)	(3.43)	(0.93)	(0.61)
_cons	-0.0111***	-0.0111***	-0.0173***	-0.0047
	(-9.96)	(-9.96)	(-14.79)	(-0.68)
N	9193	9193	9193	9193

t statistics in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Table 3: The same-month return persistence effect for October.

	(1) FMB	(2) FMB - influential outliers
lag1RETOct	0.0196	0.0181
	(0.95)	(0.87)
lag2RETOct	-0.0062	-0.0078
	(-0.31)	(-0.39)
lag3RETOct	0.0442**	0.0491**
	(2.25)	(2.54)
lag4RETOct	0.0060	0.0058
	(0.40)	(0.38)
lag5RETOct	-0.0046	-0.0056
	(-0.27)	(-0.33)
lag6RETOct	-0.0108	-0.0116
	(-0.72)	(-0.79)
lag7RETOct	0.0228	0.0227
	(1.56)	(1.56)
lag8RETOct	0.0050	0.0055
	(0.36)	(0.39)
lag9RETOct	0.0023	0.0016
	(0.15)	(0.11)
lag10RETOct	0.0196	0.0204
	(0.93)	(0.95)
_cons	0.0077	0.0077
	(0.72)	(0.72)
N	9210	9205

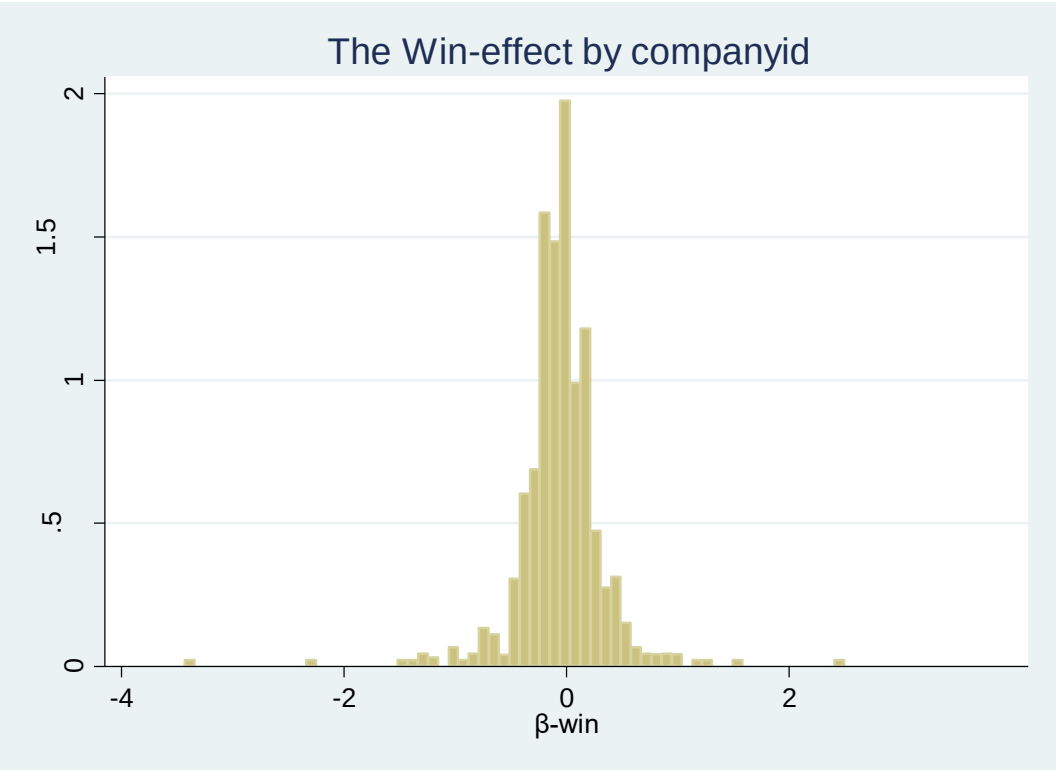
t statistics in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Table 4: The same-month return persistence effect for October.

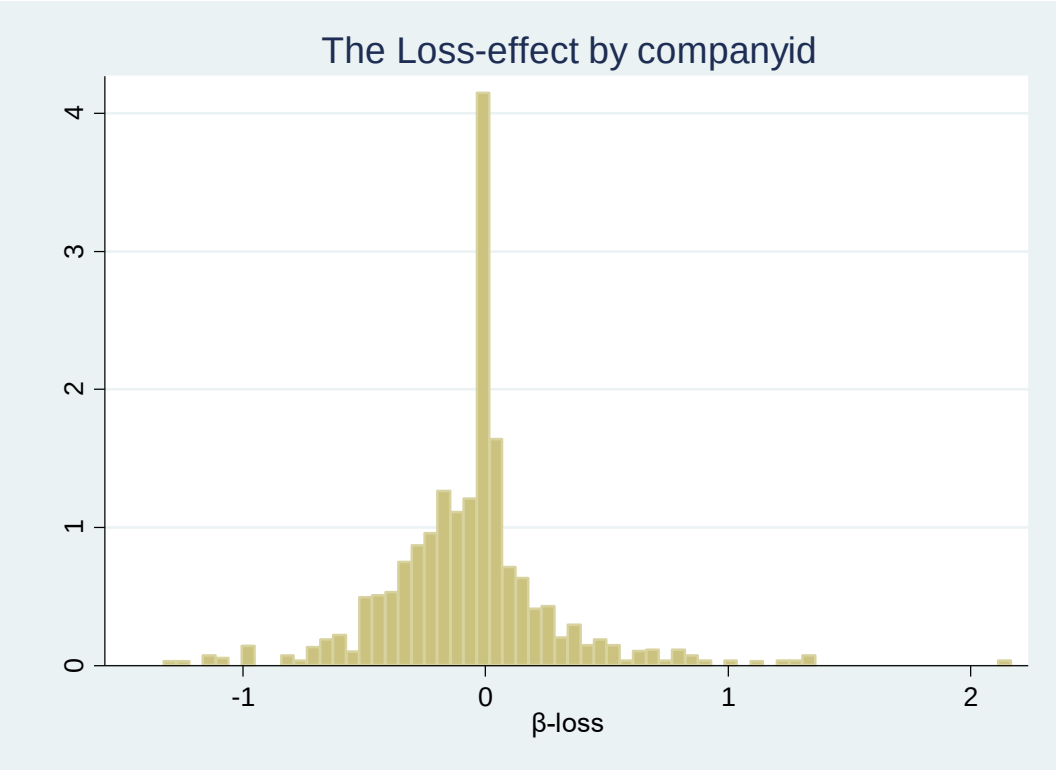
	(1) OLS	(2) GLS	(3) FE	(4) FMB
lag1RETOct	0.0115	0.0115	-0.0420***	0.0181
	(1.11)	(1.11)	(-3.96)	(0.87)
lag2RETOct	-0.0127	-0.0127	-0.0602***	-0.0078
	(-1.23)	(-1.23)	(-5.67)	(-0.39)
lag3RETOct	0.0158	0.0158	-0.0343***	0.0491**
	(1.56)	(1.56)	(-3.27)	(2.54)
lag4RETOct	0.0372***	0.0372***	-0.0063	0.0058
	(3.86)	(3.86)	(-0.63)	(0.38)
lag5RETOct	-0.0395***	-0.0395***	-0.0763***	-0.0056
	(-4.20)	(-4.20)	(-7.92)	(-0.33)
lag6RETOct	-0.0677***	-0.0677***	-0.1050***	-0.0116
	(-7.28)	(-7.28)	(-10.97)	(-0.79)
lag7RETOct	-0.1078***	-0.1078***	-0.1462***	0.0227
	(-11.82)	(-11.82)	(-15.50)	(1.56)
lag8RETOct	0.0886***	0.0886***	0.0431***	0.0055
	(9.78)	(9.78)	(4.54)	(0.39)
lag9RETOct	0.0238**	0.0238**	-0.0179*	0.0016
	(2.42)	(2.42)	(-1.76)	(0.11)
lag10RETOct	-0.0082	-0.0082	-0.0454***	0.0204
	(-0.85)	(-0.85)	(-4.53)	(0.95)
_cons	0.0132***	0.0132***	0.0181***	0.0077
	(11.87)	(11.87)	(15.83)	(0.72)
N	9205	9205	9205	9205

t statistics in parentheses
* p<0.1, ** p<0.05, *** p<0.01

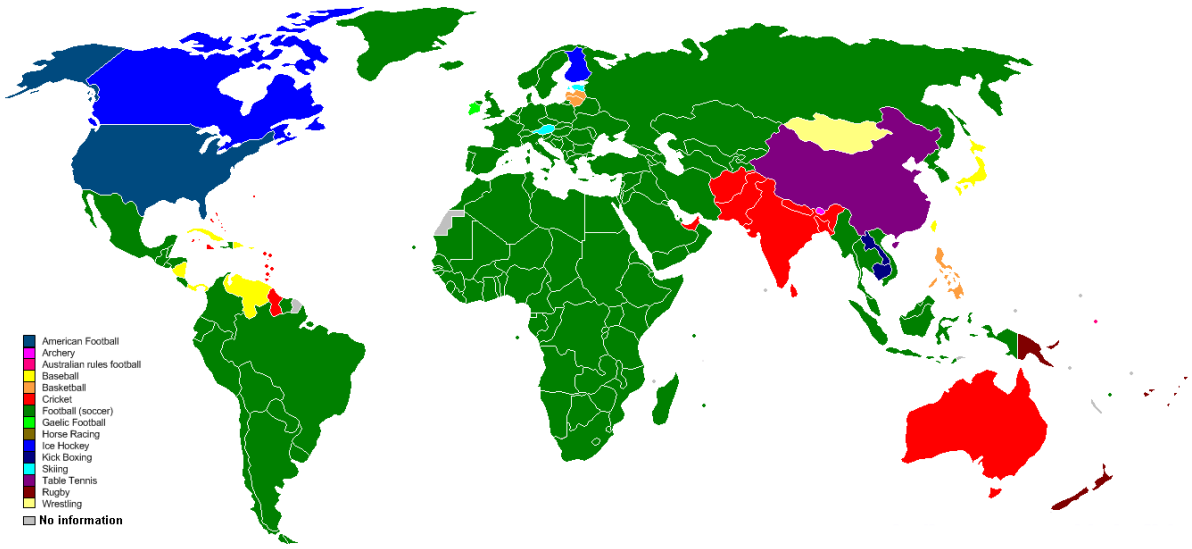
Graph 3: The magnitude of the stock response to a soccer win by company



Graph 4: The magnitude of the stock return response to soccer losses by company



Graph 5: “Soccer United the World”



Retrieved from: National Geographic (2006),

https://www.vox.com/2014/7/3/5868115/most-popular-sports-world-cup