Mood and Stock Returns

The effect of weather conditions and biorhythm on the Dutch stock market

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This thesis is submitted for the

Master of Science in Behavioural Economics

November 2016

Abstract

This master thesis investigates the influence of mood classified as investor sentiment in financial markets on Dutch stock market returns. The Dutch weather and biorhythm are used as mood-proxy variables to measure its influence on the large-cap AEX Index and the small-cap AScX Index between 2005 and 2016. The statistical significance is evaluated using Ordinary Least Squares regression analysis with Newey-West standard errors and Least Absolute Deviations. The results do not violate the efficient market hypothesis for large-cap stocks in the Netherlands. Significant effects are found for Seasonal Affective Disorder and temperature on small-cap stocks, but these regression coefficients are smaller than 0.0005.

Preface

This master thesis is the final project of my master in Behavioural Economics at the Erasmus School of Economics in Rotterdam. By writing this thesis I developed a more thorough understanding of statistics and conducting research. Also, this has been a great opportunity to combine the knowledge of behavioural economics and finance I gained during the past year. In the existing literature, different events have been examined that are associated with investor mood. I chose the weather and biorhythm, since all investors are exposed to these conditions. I enjoyed writing this thesis, especially because the results could have major practical implications.

I would like to thank dr. Han Bleichrodt for his valuable feedback, useful tips and brainstorm sessions. These insights have given me a thorough understanding of the research I conducted. Furthermore, I am very grateful for all the knowledge I gained during the master in Behavioural Economics as this has given me a broad understanding of behavioural economics, but also of finance and marketing subjects.

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Chapter 1

Introduction

For most people, a day starts when opening the curtains and looking outside. The first thing noticed is the type of weather on that day. Psychological studies have shown that the type of weather can influence a person's mood (Howarth & Hoffman, 1984). In practice, this means that people are in general happier when the sun is shining. This results in optimism when making choices and forming judgements (Schwarz, 2002). On the contrary, a bad mood stimulates detailed analytical activity, hence processing information more critically (Schwarz, 1990). In this study, the focus lies on a smaller group of people, namely investors. Since the finding of Howarth and Hoffman (1984) the weather has been used as a mood variable to measure the influence on stock market returns in several studies (Saunders, 1993; Hirshleifer & Shumway, 2003; Pardo & Valor, 2003; Kamstra, Kramer, & Levi, 2003). According to traditional finance theory stock market returns follow a random walk and cannot be determined based on past information (Fama, 1970). However, several studies found that weather conditions are significantly related to stock market returns, which cannot be explained by means of the traditional finance theory. After the finding that weather influences investor behaviour, also biorhythm variables such as length of days and daylight saving time changes became of interest. Kamstra, Kramer and Levi (2000) and Kamstra, Kramer, & Levi (2003) found a significant relationship between biorhythm and stock market returns. Behavioural finance can explain this outcome as people's behavior is not always fully rational. People deal with systematic biases when making decisions (Barberis & Thaler, 2003). One of these biases is the misattribution bias, in which people attribute the experienced feeling to the wrong cause (Ross, 1977). Misattribution of arousal or feelings is likely to be the cause of finding a significant relationship between weather and biorhythm variables and stock market returns in various studies.

Weather and biorhythm variables in relation to stock market returns in the Netherlands have not been studied yet. Therefore, I will contribute to the existing literature by extending the scope of this field of interest by examining a new time frame and different market. Thereafter, a conclusion can be drawn on whether investor sentiment significantly influences investor behaviour in the Netherlands. In case irrationality among investors is also found in the Netherlands, investors can be made aware of this misattribution bias. By being aware of this market anomaly they can anticipate and hence the anomaly will disappear. Otherwise we can hold on to the traditional finance theory which states that investors are rational. To know which explanation applies to the Dutch stock market an answer to the following research question is necessary:

What is the influence of Dutch weather and biorhythm variables on Dutch stock market returns?

The structure of this thesis is as follows: in the next section, I will review existing literature, which forms the theoretical framework and builds up to the hypotheses of this paper. Thereafter, I will explain the motivation behind the used dataset, consisting of two Dutch stock market indices and various weather and biorhythm variables. This is followed by the methodology used to examine whether the studied relationship is statistically significant. In the next section I will present the results of the statistical models and compare them with preceding studies on this subject in the Discussion. Based on these results I present the implications of my research, where after I draw conclusions on the influence of investor sentiment on Dutch stock market returns. In the final section I stress the limitations of this study and give recommendations for future research.

Chapter 2

Literature review

This chapter discusses the underlying theoretical framework of weather effects on the Dutch stock market and previous studies based on this subject. First, the efficient market hypothesis and the reason for the emergence of behavioural finance will be explained. Thereafter, the effect of mood variables on decision making will be discussed along with how this affects investors and their decision making in financial markets. These insights led to explaining mood by using weather variables and their results in other countries. The previously conducted studies give rise to a set of hypotheses for the influence of the weather on the national stock market in the Netherlands.

2.1 Market efficiency

Before the birth of behavioural finance, people held on to the traditional finance theory. In traditional finance, an agent active in financial markets is called a Homo Economicus (Mill, 1848). This means people are rational, since they listen to their preferences as described by the expected utility theory when making decisions. Agents look at maximizing their own satisfaction when buying goods or services (Bernoulli, 1954). They apply Bayes' Theorem, which describes the chance that an event will happen, based on conditions that are possibly related to the occurrence of the event (Stigler, 1986). This means that agents correctly update their beliefs when receiving new information.

For a long period, the market efficiency theory by Eugene Fama (1970) was used to explain changes in stock prices. This theory states that prices in the market fully reflect all available information (Fama, 1970). Thus, prices are equal to their fundamental value, which is the discounted sum of expected future cash flows. It assumes that the criteria for market equilibrium can be expressed in expected returns. He shows evidence that the response to new available information on the first day is unbiased. There are three types of the Efficient Market Hypothesis (EMH): strong form, semi-strong form and weak efficiency. They differ in terms of the amount of information that is reflected in the price. When speaking of the strong form, all private and public information is factored in the price. This means that insider trading cannot lead to making a profit. The semi-strong form means all public information is incorporated in the price. Lastly, weak efficiency is based on historical prices, hence past public information. As this historical information is reflected in the price, it is impossible to profit from it. EMH makes it impossible to earn excess risk-adjusted average returns. If there are irrational traders in the market with mispriced securities as a result, rational traders will notice these mispriced securities and correct it.

Although people have explained the dynamics in the financial market by means of the EMH for a long time, this theory cannot explain several anomalies in the market. Barberis & Thaler (2003) showed that many market anomalies, such as naïve diversification and the equity premium puzzle, can be explained by behavioural finance. Additionally, a range of financial bubbles have occurred in the past, which cannot be explained by the Efficient Market Hypothesis (Cheng, Raina, & Xiong, 2014; Ofek & Richardson, 2003). These financial bubbles occur when the market value rises significantly above its fundamental value, after which prices fall rapidly. According to the EMH, information is available to all agents and after a short time span implemented in the stock price, reflecting the fundamental value. Hence, in the view of traditional finance theory the so-called bubble is the change in fundamental expectations about the return of an asset. However, Cheng, Raina and Xiong (2014) showed a lack of awareness of the large-scale housing bubble by securitization agents between 2004 and 2006. EMH argues that rational agents snap up the opportunity when there is a mispricing, which results in a correction of the market price (Fama, 1970). Thus, the lack of awareness of securitization agents and hence not updating beliefs correctly, cannot be explained by the traditional finance paradigm.

Other anomalies which cannot be explained by traditional finance theory are calendar effects such as the January effect and the Monday effect. The January effect means that the average monthly stock return is higher in January compared to other months (Thaler, 1987). Investors can profit from this phenomenon by buying stocks before January and sell them during the first month of the year. The Monday effect shows a significant average negative return on Mondays. These unusual stock returns over weekends have been reported in numerous studies taking different stock indices into account (Wang, Li, & Erickson, 1997; French, 1980). However, in his study Kamara (1997) shows the decline of the Monday effect after

April 1982 for the S&P500. For a small-cap index of NSYE stocks the Monday effect is still present though. He explains this difference by the dominance of institutional investors in large stocks, as they have lower transaction costs. Individual investors trade more often in small-cap stocks and are less sophisticated, hence do not exploit the seasonal pattern. According to the efficient market theory, stock prices follow a random walk (Fama, 1970). This means that stock prices cannot be predicted using past information. However, several studies show that the day, month or time of the year can be used to predict stock market returns (Ashikh, 2012; Mehdian & Perry, 2001; Coutts & Mills, 1995).

Fama (1991) explained that it is hard to test market efficiency by introducing the joint hypothesis problem. When testing whether a market is efficient, this must be tested in combination with an asset-pricing model. This means that market anomalies can result from both a misperceived asset pricing model or market inefficiency. However, someone cannot tell which of the two phenomena explains the market anomalies.

When testing EMH one automatically tests two hypotheses. The first hypothesis is that markets are efficient. The second hypothesis is a description of what an efficient market looks like. When the efficient market hypothesis is refuted due to a market anomaly, Fama (1991) invalidates this by explaining that the anomaly can exist due to a misperceived asset pricing model or market inefficiency.

The anomalies described above suggest that economic agents do not always make rational decisions. This made researchers look for other explanations As a result, behavioural finance came into existence. It implies that some financial phenomena can be explained better by models in which some agents are not fully rational. Behavioural finance has two building blocks: limits to arbitrage and psychology (Barberis & Thaler, 2003). Limits to arbitrage means that rational agents cannot always correct the irrationality of other investors, which can have a long term and substantial impact. Psychology is about the systematic biases that emerge when people make decisions based on preferences and when forming beliefs. When beliefs are formed based on heuristics rather than Bayes' law this is called 'investor sentiment' (Shleifer, 2000). In that case agents deal with bounded rationality, meaning that the decision-maker has cognitive limitations and limitations of computational and knowledge capacity (Simon, 1997). By using heuristics, we can simplify the environment as we cannot process all information available in the market.

Researchers thought for a long time that humans make rational decisions and update their beliefs according to Bayes' theorem when new information becomes available. However, behavioural finance refutes this argument. People do not always make rational choices, contradictory to the traditional finance paradigm, resulting in financial phenomena that keep repeating themselves in the future. Behavioural finance has made sense of why a range of financial phenomena such as financial bubbles and calendar effects do exist.

2.2 Mood and decision making

Psychologists study people's behaviour and their minds. This includes research on how mood affects behaviour. The robust effect found in many studies is that people in good moods are more optimistic when making choices. When people feel good they tend to think of positive cognitions and events (Isen, Shalker, Clark, & Karp, 1978). Wright & Bower (1992) found that when a decision is sensitive to elicited subjective probabilities or preferences of the decision maker, the mood of the decision maker influences the decision. This means that people who are in a good mood are more optimistic in choices and judgments compared to people in a bad mood. Sadness signals a need for paying more attention when processing information (Schwarz, 2002). However, only mild forms of sadness lead to processing information in detail (Hartlage, Alloy, Vazquez, & Dykman, 1993). Hence, the affective state of an individual influences their way of information processing. This is called the mood-as-information theory (Schwarz, 1990). This research shows that a bad mood stimulates individuals to employ detailed analytical activity, whereas in a good mood individuals do not use the same way of detailed information processing. This does not necessarily mean that optimism is a bad thing, as it generates enthusiasm and keeps people motivated. However, there must be a balance between optimism and realism (Lovallo & Kahneman, 2003). Many studies found that emotion influences decision making when conditions of risk and uncertainty are involved (Schwarz, 1990; Forgas, 1995). The more complex or unusual the situation, the greater the influence of affective biases on a person's judgments (Forgas, 1995). As a result, Loewenstein et al. (2001) introduced the risk-as-feelings hypothesis. They show that emotional responses to uncertain situations often deviate from cognitive assessments, which are dependent on objective aspects such as the probability of events and estimates of the outcome severity of these uncertain situations. When this divergence is present, an individual's emotional state drives behaviour.

Extremes in emotional arousal, either low or high, drives bounded rationality (Kaufman, 1999). Nofsigner (2005) found that when increasing mood becomes extreme, this can lead to overconfidence, excess and euphoria. At the peak, decreasing mood is associated with pessimism, suspicion and conservatism.

From these studies, we can conclude that someone's mood influences their decision-making process, which may lead to incorrect judgments because of misattribution of arousal. This means that people attribute their experienced arousal or feelings to a wrong cause resulting in an attribution error (Ross, 1977). An example of this misattribution is that research shows that people feel happier on sunny days compared to cloudy days. From a financial perspective, this can also imply important lessons for financial markets. In which way investor mood can have implications for market fluctuations will be discussed in the next section.

2.3 Investor sentiment and stock pricing

Contradictory to the Efficient Market Hypothesis, an increasing number of studies confirms the finding of Schwarz (1990) that stock prices are not only influenced by new information, but also by investor sentiment (Kahneman & Tversky, 1979; Bollen, Mao, & Zeng, 2011). Barber & Odean (2001) found that investors looking on the internet for information have access to three billion pieces of information. Because of bounded rationality we are not able to process all this information and update our beliefs accordingly. Preis, Moat and Stanley (2013) found that the frequency of Google search requests for key words regarding financial markets increased before a stock market crash. This could be explained by the investors' desire to gather more information about stocks when they are concerned.

Our affective state influences the process of making a satisfactory decision. Modelling market dynamics is complex (Schumaker & Chen, 2009). Stock prices are driven by many different factors. To reduce the complex task of determining probabilities and forecast values to simpler subjective operations, people use heuristics (Tversky & Kahneman, 1974). Meaning that although new information becomes available, people are not able to review all this information and update their beliefs accordingly.

Zhang and Fishbach (2005) also show that emotions influence financial decisions. Sellers endowed with an object experience loss aversion when they are selling the object. In practice this means that a higher price is asked when selling the object, in comparison to what someone would bid to obtain it (Kahneman, Knetsch, & Thaler, 1990). Shu (2010) shows that equity and bill prices are positively correlated with investor mood. Here, asset prices are higher when the investor is in a better mood. Cohen-Charash, Scherbaum, Kammeyer-Mueller and

Staw (2013) researched whether press reports about the collective mood of financial market agents can predict stock market returns. They found that investors' emotion on the previous trading day can predict the opening price of the NASDAQ today. A pleasant mood leads to higher opening prices, whereas an unpleasant mood leads to lower opening prices. Social media show a similar pattern. By examining specific public mood dimensions in Twitter feeds, the daily volatility in closing values of the Dow Jones Industrial Average (DJIA) can be predicted with 87.6% accuracy (Bollen, Mao, & Zeng, 2011). By using text processing techniques, they classified tweets into a range of moods. These moods showed a correlation with the closing prices of the DJIA. Au, Chan, Wang and Vertinsky (2003) induced good and bad moods by priming to examine whether this influences traders in financial markets. They found that traders in a good mood lost money, whereas traders in a neutral or bad mood made profit. When traders were in a good mood they made less accurate decisions. They also suffered from overconfidence resulting in taking unwarranted risks. Although mood as a variable does not play a role in the traditional finance paradigm, these results, confirming the mood-as-information theory by Schwarz (1990), indicate that integrating investor mood into asset-pricing models can improve the prediction of investor behaviour (Shu, 2010). To develop a method to measure and predict mood, further research on how investor mood influences asset prices is required.

As previously discussed, many studies show the relationship between mood and decision making. Nofsinger (2005) complemented this by showing the difference in time lag in which social mood influences the financial market. To match changes in social mood, the stock market changes quickly to reflect these adjustments. However, the time lag for good and bad moods is different. The time lag is shorter for decreases in stock market returns and business activity due to pessimism compared to increases in business activity due to increases in mood. This can be explained by the fact that stopping mergers and IPOs can be carried out more quickly than initiating and finalizing them.

Predicting stock market returns by looking at events

To investigate whether mood influences stock market returns, various researchers looked at events that influence investor mood. Johnson & Tversky (1983) conducted an experiment that shows that when participants read about a happy event this leads to a positive mood, which then results in an overall decrease in risk perception. On the contrary, reading about a specific fatal event led to a pervasive rise in participants' estimates of risk and other unwanted events. This misattribution bias could cause market mispricing (Hirshleifer, 2001). Hence, an individual's mood also influences the amount of risk he is willing to take. If investors wrongly evaluate a stock's earnings prospects to the stock's return prospects favorably this leads to overpriced growth stocks (Lakonishok, Shleifer, & Vishny, 1992). This finding cannot be explained by the traditional finance paradigm.

Another often researched area when examining the relationship between mood and stock returns are sports events. Ashton, Gerrard and Hudson (2003) found a significant relationship between the results of the English football team and the returns of the FTSE100 index, which represents 100 companies with the largest market capitalization listed on the London Stock Exchange. They found that wins are followed by favorable stock returns and vice versa. Edmans, Garcia and Norli (2007) examined the relationship between sports games and stock market returns based on psychological evidence that sports games have a strong influence on mood. They found a significant relationship between the two variables. The stock market located in the country of the losing soccer team reacts negatively when the national soccer team loses. The decline in stock market returns associated with the loss of a soccer match exceeds 7%. This loss effect is not only present for soccer, but also for basketball, cricket and rugby. Contrary to the findings of Ashton, Gerrard and Hudson (2003), when the national soccer team wins, this does not lead to a rise in the national stock market. This is in line with the theory of loss aversion, where losses are given more weight than wins. The found that the loss effect cannot be justified by financial decisions made by rational agents, as the effect is not priced into the stock market index in case a defeat is expected. Therefore, investor mood due to sports results is interpreted as the cause of a change in stock prices.

On the contrary, Klein, Zwergel, & Heiden (2009) do not find a statistically significant relationship between World and European championship soccer match results and nation stock returns. This gives rise to the belief that the market is efficient and contradicts the mood-as-information theory by Schwarz (1990).

Yuan, Zheng and Zhu (2006) used the position of the moon as input for an event to test stock market returns. They investigated the belief in lunar effects by examining the consequences associated with stock market returns. According to psychological studies, full moon phases are associated with depressed mood. Therefore, they examined whether full moon phases lead to lower stock market returns. Since ancient time different moon phases have been associated with mental disorder. As lunar cycles are predictable, the possible existence of a causal relationship between lunar cycles and stock returns violates the efficient market hypothesis. Their stock market return sample consists of 48 countries, which is the dependent variable in their regression analysis. A lunar dummy variable is used as the explanatory variable indicating a full moon phase or new moon phase. Their results show that new moon phases are correlated with higher stock market returns. Looking at 15-day and 7-day windows, returns of the new moon periods are 3.95 basis points and 5.93 basis points higher respectively than returns of the full moon periods. This effect is the strongest for emerging market countries. The change in returns cannot be explained by market volatility or trading volumes. Additionally, the lunar effect is independent of other calendar anomalies such as the day-of-the-week effect.

The traditional finance paradigm assumes that investors correctly change their beliefs according to Bayes' law when new information becomes available. However, most the previously described studies shows that new information is not the only cause of a change in stock market returns. Investor sentiment also plays a role, which supports the mood-as-information theory presented by Schwarz (1990). Behavioural finance can help to explain the outcomes of these studies. It is built around the belief that people are not always fully rational when making decisions.

Another area that is often studied to research the relationship between mood and stock returns is the effect of the weather. In the next section this research area will be explained in more detail.

2.4 Weather as a mood variable

Many people would agree with the statement that the weather is not related to economics, but appearances can be deceptive. In psychology it has been recognized that the weather influences someone's mood. Howarth and Hoffman (1984) found that, of all weather effects, the effect of humidity, hours of sunshine and temperature on mood is greatest. For example, a high level of sunshine is positively related with mood. Generally, it can be said that sunshine causes people to be happier. On the contrary rain is likely to make people feel less satisfied with their life (Schwarz & Clore, 1983). This means that when we are carrying out the difficult task of rating our life satisfaction, the result will depend on our current mood. This is even true when factors that influence our mood, e.g. the weather, do not influence a person's personal life satisfaction directly. For example, it was found that sunshine is positively correlated with the generosity of restaurant visitors when tipping the waitress (Cunningham, 1979). Additionally, sunshine and temperature are significantly related to self-reported mood.

Saunders (1993) studied the relationship between the weather in New York City and financial decisions. He used six types of meteorological data (temperature, relative humidity, precipitation, wind, sunshine, and cloud cover) in relationship with daily percentage changes in the Dow Jones Industrial Average and equal- and value-weighted daily percentage changes of the NYSE/AMEX index. He found a significant relationship between the level of cloud cover and the change in stock prices, indicating that cloudy days negatively affect mood resulting in lower stock prices and vice versa. His findings are robust for the January and Monday effect.

Hirshleifer and Shumway (2003) complemented Saunders' research by finding that sunshine is also significantly correlated with stock returns. Based on these results, traders facing low transaction costs could profit from using weather based strategies (Hirshleifer & Shumway, 2003). They show that trading on the weather can lead to an increase in the Sharpe ratio. However, it is hard to profit from a weather based strategy, as the weather is quite unstable. This requires frequent trading, which increases transaction costs and makes it likely to exceed the profit made by trading on the weather. The finding that weather influences mood and thus stock prices, cannot be explained by means of the traditional finance paradigm. It gives reason to believe that people do not make fully rational decisions in the financial market.

Krämer and Runde (1997) replicated Saunders' study for the German stock market, but found contrary effects. They found evidence for their hypothesis that the local weather does not influence short-term stock market returns when they do not engage in data mining. They pose a type I error to explain why Saunders' results are significant. Also, the redefinition of weather variables can change their results from insignificant into significant for most days of the week.

Trombley (1997) also replicated Saunders' study and found, like Krämer and Runde (1997), contrary evidence. His study shows that statistically significant effects depend on which returns are compared. Additionally, he found no difference between sunny day returns and rainy or cloudy day returns. These findings give rise to the belief that weather effects might be sample specific or phony. Although he does not completely reject the existence of a weather effect, he does not agree with Saunders' evidence of the weather effect. Pardo and Valor (2003) do not find a correlation between humidity and the Madrid Stock Exchange and sunshine hours and the Madrid Stock Exchange. They argue that the market can be explained by rational agents, which is coherent with the traditional finance theory.

Cao and Wei (2005) investigate the relationship between temperature and stock market returns. They hypothesize that lower temperature is related to higher stock market returns based on evidence that suggests that lower temperature can lead to aggression resulting in more risk-taking. Higher temperature is related to higher or lower stock returns; as high temperature can lead to aggression or apathy. As both emotions have contrary effects, this can lead to either high or low returns. For their research, they used nine stock market indices located in eight different countries. They found a temperature anomaly, as stock market returns and daily temperature are negatively correlated across the whole range of temperature. This result shows that apathy has a stronger effect than aggression when temperature is high. On the contrary, low temperatures lead to aggression. When taking other anomalies such as the Monday effect and Seasonal Affective Disorder (SAD) effect into account, the temperature is still negatively correlated with stock returns. A study by Floros (2011) confirms the temperature effect as well in Portugal. He found a statistically significant relationship between daily stock prices of the PSI20 index and temperature from 1995 to 2007.

Table 2.1 Summary of previous studies on the influence of the weather on stock market returns.

Researcher(s)	**Country**	**Weather variable(s)**	**Correlation weather variable and stock market returns**
Saunders (1993)	United States	Cloud cover	Yes, negative
Krämer and Runde (1997)	Germany	Cloud cover Atmospheric pressure Humidity	No No No
Trombley (1997)	United States	Cloud cover	No
Hirshleifer and Shumway (2003)	26 different financial markets (e.g. Greece, South-Africa and the United States)	Hours of sunshine	Yes, positive
Pardo and Valor (2003)	Spain	Hours of sunshine Humidity	No No
Cao and Wei (2005)	8 different financial markets (e.g. the United States, Britain and Germany)	Temperature	Yes, negative
Floros (2011)	Portugal	Temperature	Yes, negative

The research on weather related mood proxy variables has been expanded by relating biorhythms to stock market returns. Biorhythms may cause fluctuations in mood, which can be misattributed by investors and guide them while making financial decisions. An application of the effect of biorhythms on the stock market is carried out by Kamstra et al.

(2003). They examine the effect of Seasonal Affective Disorder (SAD) on the stock market. Clinically, SAD is a depressive disorder caused by seasonal variation in hours of daylight in a day. From experimental research, it is known that depression in general is linked to a higher level of risk aversion (Zuckerman, 1994; Eisenberg, Baron, & Seligman, 1998). When applied to the weather, this means that when the hours of sunlight during the day decrease, people are more likely to sell their risky assets. Therefore, the authors hypothesize a causal relationship between SAD and stock market returns. Four stock indices from the United States are used and indices from eight other countries to research broad-based economies at different latitudes and from both hemispheres. To measure SAD, they use the number of hours during the night, defined as the hours between sunset and sunrise. They found a statistically significant effect of SAD on stock market returns for all countries except for Australia. For the most part this is more significant for countries further from the equator, as seasonal variation in daylight is smaller when a country is located closer to the equator.

Before this study, Kamstra, Kramer and Levi (2000) already conducted another study on biorhythm. Triggered by the finding that sleeping disorders can lead to depression (Coren, 1996), they researched the impact of Daylight Saving Time Changes (DSTCs) on the financial market mechanism. They examined the effect during two weekends every year, one in Spring when the clocks go forward one hour and one in Autumn when the clocks go back one hour. The link between the time change and stock market returns might come from anxiety. The anxiety is a result of having difficulty solving problems and making rational decisions on the first trading day following the time change. This anxiety can result in a decrease in stock prices. Although the Monday effect is recognized as an anomaly, the market returns on a Monday after a DSTC are significantly more negative. This effect was found in the UK, US and the Canadian market. In Germany the effect was not found, but this might be due to a lack of data.

Table 2.2 : Summary of previous studies on the influence of biorhythm on stock market returns

Researcher(s)	**Country**	**Biorhythm variable(s)**	**Correlation biorhythm variable and stock market returns**
Kamstra et al. (2003)	9 countries, located in the Southern or Northern hemisphere	Seasonal Affective Disorder (SAD)	Yes, positive
Kamstra, Kramer and Levi (2000)	Unites States, Canada, United Kingdom and Germany	Daylight Saving Time Changes (DSTCs)	Yes, negative

2.5 My research

To qualify for a mood variable, the variable must satisfy three key characteristics to justify studying its relationship with stock movements (Edmans, García, & Norli, 2007). Firstly, the mood variable, the Dutch weather in my case, must influence mood in a substantial and unambiguous way, which will affect asset prices. Howarth and Hoffman (1984) and Schwarz & Clore (1983) showed that the weather influences someone's mood substantially. Secondly, the variable must be of impact on many people's mood so that it affects a large portion of investors. Lastly, the effect needs to be correlated across most citizens within a country. As all Dutch citizens are affected by the weather conditions, this also includes investors. This satisfies the second condition. A great number of citizens in the Netherlands participate in buying and selling stocks. In case the effect of mood on stock market returns is found, this affects many Dutch citizens, satisfying the third condition. The impact of the weather on mood has been extensively researched. However, due to contradictory evidence across countries and weather variables, as can be quickly seen from Table 2.1, an unambiguous conclusion has not been drawn yet. In this Master thesis, I will contribute to existing studies by investigating the influence of the weather in the Netherlands, influenced by four seasonal cycles on mood as described in the first condition.

2.6 Sub questions

Numerous studies have been conducted investigating the effect of the weather on stock returns. Many researchers examined this relationship in the United States (e.g. Saunders 1993; Cohen-Charash, Scherbaum, Kammeyer-Mueller, & Staw, 2013), but also various studies have been conducted researching the weather effect on the European stock market (e.g. Pardo & Valor, 2003; Krämer & Runde, 1997). As the studies give contrary outcomes, the weather effect might be sample specific. Therefore, this thesis contributes to existing literature by examining the possible influence of the Dutch weather on the Amsterdam Exchange Index (AEX). This is the most important indicator of the Dutch stock market as it is composed of the 25 most actively traded securities with the largest market capitalization on the NYSE Euronext Amsterdam. Additionally, the Amsterdam Small Cap Index (AScX) will also be taken as a dependent variable, since previous studies indicated that the impact of mood proxy variables on stock market returns is especially present for small-cap stocks (Edmans, García, & Norli, 2007; Krivelyova & Robotti, 2003). Only taking the AEX as the dependent variable might give a weaker result.

Kamstra, Kramer, & Levi (2003) studied whether biorhythm influences the US stock market. However, whether biorhythm effects are present in the Dutch stock market has not been examined yet. To examine the possible existence of weather and biorhythm effects in the Netherlands, the sub questions below will be studied, to answer the main research question. The questions are based on the findings of previous studies.

Q1. Are various weather conditions significantly correlated with the daily returns of the AEX and AScX?

- *Q1.1. Is there a significant relationship between temperature and daily returns of the AEX and AScX index?*
- *Q1.2. Is there a significant relationship between humidity and daily returns of the AEX and AScX index?*
- *Q1.3. Is there a significant relationship between cloud cover and daily returns of the AEX and AScX?*
- *Q1.4. Is there a significant relationship between hours of sunshine and daily returns of the AEX and AScX?*

Q2: Does biorhythm influence daily returns of the AEX and AScX?

As discussed before, Schwarz (1990) introduced the mood-as-information theory, explaining that an individual's affective state influences their way of information processing. An individual's bad mood stimulates him/her to evaluate his/her activities critically and engage in detailed information processing. However, when in a good mood, individuals tend to be not as critical when processing information. Therefore, the following question should be answered:

Q3: Are investors in a good mood more easily affected by mood variables compared to investors in a bad mood?

I will explain the methodological approach and the corresponding data used to answer these questions in the next chapter.

Chapter 3

Data and Methodology

In the data section I will discuss the variables used to answer the previously described sub questions. In the Methodology section, I will elaborate upon the statistical methods I will use to answer the research question.

3.1 Data

3.1.1 Daily stock market returns

Similar to the study of Saunders (1993), the financial data to measure possible weather effects consist of daily closing values. In this study the percentage change in daily closing values of the AEX and AScX indices is used as the dependent variable in the period from the 1st of January 2006 until the 31st of December 2015. The financial data is retrieved from Datastream. As the Amsterdam Stock Exchange is closed during the weekend, the percentage change on Monday is calculated by comparing its value to the closing value on the previous Friday.

3.1.2 Weather related mood-proxy variables

The weather data is retrieved from the website of the Koninklijke Nederlands Meteorologisch Instituut (KNMI), which is a meteorological institution led by the Dutch ministry of infrastructure and environment. All weather variables are measured daily in De Bilt, a small city in the middle of the Netherlands. From the reviewed literature, various weather variables are chosen to explain a possible mood change. In many studies, cloud cover is used as a mood-proxy variable (Dowling & Lucey, 2005; Saunders, 1993; Trombley, 1997; Krämer & Runde, 1997). Saunders (1993) shows that there is a negative correlation between cloud cover and the DJIA and the NYSE/AMEX index. Dowling and Lucey (2005) also find this negative correlation in the Irish stock market. However, Trombley (1997) and Krämer and Runde (1997) do not find a significant correlation between cloud cover and stock returns in the United States and Germany respectively. To examine whether there is a significant relationship between cloud cover and Dutch stock market returns, I will include this variable in the analysis. The cloud cover variable is defined by the KNMI as a number from 0 to 8, of which 5.43 is the mean. The number 0 means that there are no clouds and 8 means that the sky is completely covered with clouds. A change from 1 to 2 comes down to an absolute increase of 12.5% in cloud cover. Howarth and Hoffman (1984) show that the effect of humidity, hours of sunshine and temperature are greatest on mood. Therefore, these three variables are included in the analysis as well. For humidity, the daily mean relative atmospheric humidity in percentages is used, which ranges from 30% to 100%. The mean daily percentage of humidity is 80.77%. Sunshine is expressed in sunshine duration calculated from global radiation. The values range from 0 to 15.3 hours per day, where the average hours of sunshine per day is 4.77 between 2005 and 2015. The mean daily temperature in the Netherlands during the period of interest was 10.7 degrees Celsius, which corresponds to the value of 107 in the data set, and ranged between -12.1 and 27.1 degrees Celsius in the timeframe of interest.

3.1.3 Biorhythm variables

To measure whether biorhythm influences Dutch stock market returns, I examine the effect of Seasonal Affective Disorder (SAD) and the impact of Daylight Saving Time Changes (DSTC). For the SAD variable, I use the formula introduced by Kamstra, Kramer and Levi (2003). As the Netherlands is part of the Northern Hemisphere, the formula to measure the time between sunset and sunrise is $24 - 7.72 \times arcos[-tan(\frac{2\delta\pi}{360})\tan(\lambda)]$[1] SAD_t indicates the length of a night at time t in fall and winter relative to the mean annual length of hours per night. This equals the value of the outcome of the previously described formula minus 12 (this is the annual mean of the number of hours during a night) during fall and winter (from the 21$^{\text{st}}$ of September until the 20$^{\text{th}}$ of March) and 0 otherwise. Kamstra, Kramer and Levi (2003) show that stock returns decrease during the fall, because of the diminishing hours of daylight which is associated with depression leading to risk aversion. After the winter solstice, the amount of daylight increases, which positively affects stock market returns.

[1] In this equation, the variable δ represents the latitude of Amsterdam, which is the city where the National Stock Exchange is located. λ represents the sun's declination angle calculated as $0.4102 \times sin[(\frac{2\pi}{365})(julian - 80.25)]$, here "julian" is a variable ranging from 1 to 365, and 366 in a leap year. (Kamstra, Kramer, & Levi, 2003). Leap years in the dataset include 2008 and 2012.

Therefore, a positive relationship between SAD_t and Dutch stock market returns is expected.

Previous research showed that stock market returns on a Monday after a DSTC are significantly more negative compared to other Mondays in the UK, US and the Canadian market (Kamstra, Kramer, & Levi, 2000). For the German stock market the effect was not found. In this thesis, the interest lies in the effect of DSTC on stock market returns in the Netherlands. To measure the effect, I create a dummy variable, which takes the value of one on a Monday following a daylight saving time change and zero otherwise. As most countries show a negative relationship between DSTC and stock market returns, the Monday after a shift in time is expected to result in lower stock returns compared to Mondays without this time shift.

3.1.4 Good and bad mood variables

To test whether investors are in a good or bad mood, I use the mood indicator introduced by Dowling and Lucey (2005). They use derived variables for both types of mood. They argue that mood is a result of historical stock returns. Therefore, they take long-run (200-day) and short-run (10-day) moving averages into account. Investors are said to be in a good mood when the short-run moving average is above the long-run moving average. Investors are said to be in a bad mood when the short-run moving average is below the long-run moving average.

3.1.5 Control variables

Apart from weather related mood-proxy variables, several control variables are included to predict Dutch stock market returns. In this thesis the interest does not lie in the control variables, but it is necessary to include these variables in the analysis to accurately examine the effect of the mood-proxy variables on stock market returns.

MSCI World Index

The MSCI World Index will be used as a determinant for both Dutch stock market indices used in this study. The MSCI World Index captures large- and mid-cap stocks from 23 developed market countries[2]. Due to the lack of barriers to portfolio flows both in mature and emerging markets and the determination of risk premiums on a global level, co-movements of stock prices worldwide are more frequently noticed (Dutt & Mihov, 2013). The mean of

[2]The developed market countries include: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the UK and the US (MSCI Inc., 2016).

country pair correlations of 58 countries based on MSCI indices was greater than 0.6 in 2006. From this research it follows that local stock markets are correlated with other countries' stock market indices. To correct for this correlation, the percentage change of the MSCI World Index is included, as the Dutch stock market indices are likely to be influenced by foreign stock exchanges. The difference in movements between the MSCI World Index and the Dutch stock indices might be explained by the weather and hence mood.

One day lagged stock market return

In previous studies one day lagged stock market returns are included to predict stock exchanges. Cao and Wei (2005) use the one day lagged return, r_{t-1}, to control for first order autocorrelations. Saunders (1993) also included r_{t-1} to account for nonsynchronous trading effects. Therefore, I also included r_{t-1} in this research to control for steadfastness of stock price movements.

Dummy variables

In previous studies where the relationship between investor sentiment and stock market returns is examined, robustness checks are performed for documented anomalies. To control for these anomalies, dummy variables must be used. This means that a variable will have the value of either one or zero, which indicates whether a specific condition is satisfied. In existing literature, the January and Monday effect, as discussed in the first chapter, are controlled for by using a dummy variable (Saunders, 1993; Yuan, Zheng, & Zhu, 2006; Dowling & Lucey, 2005). Also in this master thesis, the January effect and Monday effect will be corrected for. For the Monday effect the value of one will indicate that the reported daily return is from a Monday and zero otherwise. For the January effect the value will be one for daily returns in the month January and zero for the eleven other months of the year.

3.2 Methodology

To test the relationship between the weather and stock market returns, ordinary least squares regression analysis is commonly used in the literature (Saunders, 1993; Cao '& Wei, 2005; Dowling & Lucey, 2005). Dowling and Lucey (2005) perform Ordinary Least Squares (OLS) regression analysis with White heteroskedasticity-consistent standard errors. As they find non-normality in the data, Least Absolute Deviation (LAD) and Trimmed Least Squares (TLS) regressions are used to reanalyze the data. Hirshleifer and Shumway (2003) also use OLS regressions in combination with a logit model that relates various weather variables with the probability of a positive daily stock return. Another method to examine the relationship between the weather and its effect on stock market returns is the Autoregressive Conditional Heteroskedasticity (ARCH) model. This model is built on the assumption that the variance of the current error term is linked to the error terms of previous periods, which leads to volatility clustering. This includes the simple GARCH (1,1) model used by Kang, Jiang, Lee, & Yoon (2010) to measure the relationship between weather and volatility of the Shanghai stock market. As the focus of this Master thesis is the weather effect on stock market returns instead of volatility, the OLS regression will be used. Nevertheless, in case heteroskedasticity is found, standard errors that correct for heteroskedasticity will be used. Additionally, as this research deals with time series data in a regression analysis, stationarity is required. Therefore, the Augmented Dickey-Fuller unit root test is conducted (Dickey & Fuller, 1981). The null hypothesis states that a unit root is present in the series, whereas the alternative hypothesis is that the time series is stationary.

3.2.1 Regression models to test the research question

To examine possible weather and biorhythm effects on Dutch stock market returns, various questions are defined in the previous chapter. To answer these questions I use regression analysis. To test Q1 and Q2 the dependent variable is the percentage change of the daily closing values of the AEX and AScX index. I include the same control variables (percentage change of the MSCI World Index, Monday dummy, January dummy and one day lagged returns of either the AEX or AScX index) in all regressions. The control variables reduce the risk of a regression analysis which suffers from the omitted-variable bias. In this study this would mean an over- or underestimation of mood-proxy variables, because of other omitted variables. Including the previously mentioned control variables improves the predictive power of the regression models.

The setup of the explanatory variables is different for the sub questions. First I will test the effect of Dutch weather on the AEX and AScX index by estimating an overall model, which includes both weather and control variables. The choice for the weather variables (temperature, humidity, cloud cover and sunshine) are explained in the Data section.

Secondly, I will test the effect of biorhythm as a mood proxy variable on the daily returns of the AEX and AScX index. I will follow the same approach as when testing the influence of the weather variables, since an overall model is estimated including the biorhythm variables SAD and DSTC and the same control variables as in the weather model.

A different approach is used to test Q3. The dependent variable is investor mood, which is a derived variable. The dependent variable takes the value of the percentage change in daily returns of the AEX or AScX index when being in either a good or bad mood. As previously defined, investors are said to be in a good mood when the short-run (10-day) moving average is above the long-run (200-day) moving average. If this is the case, the dependent variable takes the value of the percentage change of the daily closing values of the AEX or AScX index, otherwise it takes the value of zero. Investors are said to be in a bad mood when the short-run (10-day) moving average is below the long-run (200-day) moving average. Therefore, when the long-run moving average is higher than the short run moving average, the dependent variable takes the value of the percentage change in daily return of the AEX or AScX index and zero otherwise. Both in the good and bad mood regression models, all mood proxy variables and control variables are combined in one model.

The regression equations below are the estimated models which examine the relationship between weather variables and Dutch stock market returns, biorhythm variables and Dutch stock market returns and the effect of weather and biorhythm variables on investor mood.

Weather Model

$$R_{\text{AEX t}} = \beta_1 + \beta_2 Temperature_{\text{t}} + \beta_3 Humidity_{\text{t}} + \beta_4 Cloud_{\text{t}} + \beta_5 Sunshine_{\text{t}} + \beta_6 R_{\text{AEX t-1}} + \beta_7 R_{\text{MSCI t}} + \beta_8 Monday_{\text{t}} + \beta_9 January_{\text{t}}$$

$$R_{\text{AScX t}} = \beta_1 + \beta_2 Temperature_{\text{t}} + \beta_3 Humidity_{\text{t}} + \beta_4 Cloud_{\text{t}} + \beta_5 Sunshine_{\text{t}} + \beta_6 R_{\text{AScX t-1}} + \beta_7 R_{\text{MSCI t}} + \beta_8 Monday_{\text{t}} + \beta_9 January_{\text{t}}$$

Biorhythm Model

$$R_{\text{AEX t}} = \beta_1 + \beta_2 SAD_{\text{t}} + \beta_3 DSTC_{\text{t}} + \beta_4 R_{\text{AEX t-1}} + \beta_5 R_{\text{MSCI t}} + \beta_6 Monday_{\text{t}} + \beta_7 January_{\text{t}}$$

$$R_{\text{AScX t}} = \beta_1 + \beta_2 SAD_{\text{t}} + \beta_3 DSTC_{\text{t}} + \beta_4 R_{\text{AScX t-1}} + \beta_5 R_{\text{MSCI t}} + \beta_6 Monday_{\text{t}} + \beta_7 January_{\text{t}}$$

Mood model

$$R_{\text{GoodMood AEX t}} = \beta_1 + \beta_2 Temperature_{\text{t}} + \beta_3 Humidity_{\text{t}} + \beta_4 Cloud_{\text{t}} + \beta_5 Sunshine_{\text{t}} + \beta_6 SAD_{\text{t}} + \beta_7 DSTC_{\text{t}} + \beta_8 R_{\text{AEX t-1}} + \beta_9 R_{\text{MSCI t}} + \beta_{10} Monday_{\text{t}} + \beta_{11} January_{\text{t}}$$

$R_{\text{GoodMood AScX t}} = \beta_1 + \beta_2 Temperature_{\text{t}} + \beta_3 Humidity_{\text{t}} + \beta_4 Cloud_{\text{t}} + \beta_5 Sunshine_{\text{t}} + \beta_6 SAD_{\text{t}} + \beta_7 DSTC_{\text{t}} + \beta_8 R_{\text{AScX t-1}} + \beta_9 R_{\text{MSCI t}} + \beta_{10} Monday_{\text{t}} + \beta_{11} January_{\text{t}}$

$R_{\text{BadMood AEX t}} = \beta_1 + \beta_2 Temperature_{\text{t}} + \beta_3 Humidity_{\text{t}} + \beta_4 Cloud_{\text{t}} + \beta_5 Sunshine_{\text{t}} + \beta_6 SAD_{\text{t}} + \beta_7 DSTC_{\text{t}} + \beta_8 R_{\text{AEX t-1}} + \beta_9 R_{\text{MSCI t}} + \beta_{10} Monday_{\text{t}} + \beta_{11} January_{\text{t}}$

$R_{\text{BadMood AScX t}} = \beta_1 + \beta_2 Temperature_{\text{t}} + \beta_3 Humidity_{\text{t}} + \beta_4 Cloud_{\text{t}} + \beta_5 Sunshine_{\text{t}} + \beta_6 SAD_{\text{t}} + \beta_7 DSTC_{\text{t}} + \beta_8 R_{\text{AScX t-1}} + \beta_9 R_{\text{MSCI t}} + \beta_{10} Monday_{\text{t}} + \beta_{11} January_{\text{t}}$

Multi-collinearity

When running the regressions, multi-collinearity should be considered. When multi-collinearity is present, there are increased standard errors of estimates of the betas. This can result in insignificance of various independent variables, while they should be significant. Hence, lower standard errors increase the likelihood of a significant variable. By looking at the Variance Inflation Factor (VIF) and tolerance, a conclusion can be drawn on multi-collinearity. The VIF shows the increase of the variance due to the absence of independence between the independent variables. The tolerance is calculated by dividing one by the value of the VIF. A tolerance smaller than 0.10 gives an indication of a serious collinearity issue. When the tolerance is smaller than 0.20 a careful look at the regression model is necessary (Menard, 1995).

3.2.2 Gauss-Markov conditions

In order to perform an OLS regression the Gauss-Markov theorem must be considered. This theory states that the ordinary least squares estimators are the best linear unbiased estimators (BLUE) when the conditions of Gauss-Markov are satisfied. In this section the conditions that need to be met by the residuals will be discussed. Also, I will test whether the conditions in the regression models are satisfied.

Linearity

Linearity means that the relationship between the dependent an independent variable must be a straight line. This condition must be satisfied, as a non-linear relationship increases the likelihood of Type I and Type II errors (Osborne & Waters, 2016). For each regression, scatter plots of the residuals are used to test whether the mean of the residuals equals zero.

Homoscedasticity

This condition states that the variance of the error term must be equal for all independent variables. If this is not the case there is heteroskedasticity. This means that the variance of the error term changes when the values of the independent variables change. This results in inefficient estimates of the beta's, unreliable hypothesis tests and biased standard errors (Pedace, 2013). To test whether the regressions satisfy homoscedasticity, I performed the Breusch-Pagan test. The null hypothesis suggests homoscedasticity in the OLS. When the p-value is below 0.05, the null hypothesis is rejected and heteroskedasticity is present. In case the errors are heteroskedastic I will use robust Newey-West standard errors in the regressions to allow the fitting of the model.

Normality of residuals

One of the assumptions of regression analysis is that the data should be normally distributed, as non-normality undermines the standard tests of significance (Chatterjee & Had, 2012). Residuals must have a normal distribution for every combination of values of the independent variables. When looking at the descriptive statistics in Table 3.1 and Table 3.2, the p-value smaller than 0.05 of the Jarque-Bera test statistic shows that the data is non-normally distributed. However, when the sample size is large enough (more than 30 or 40 observations), violation of the normality assumption does not result in major problems (Elliott & Woodward, 2007). This means that parametric tests can still be performed in case of non-normality. Since the data set consists of different data points gathered on 2609 days, the central limit theorem confirms that the sample is large enough to assume normality of the residuals.

Following the methods used by Dowling and Lucey (2005), in addition to the OLS, I also run the least absolute deviation (LAD) regression to control for the non-normality in the data. The difference between OLS and LAD is that LAD estimates the coefficients that minimize the sum of the absolute residuals, whereas OLS estimates the coefficients that minimize the sum of squared residuals. LAD is a robust regression resistant to outliers. This means that the regression is insensitive to small deviations from assumptions that the model requires from the data (Huber, 1981). In the LAD regression, equal emphasis is given to all data points. Also, the LAD regression is robust to Gaussian assumptions referring to the way errors are processed in the model (Koenker & Bassett Jr., 1982).

Table 3.1 Descriptive statistics of the AEX index

AEX	
Number of observations	2608
Mean	0.000098
Standard deviation	0.000273
Skewness	0.047
Kurtosis	8.40
Jarque-Bera test statistic	3175.107123 (0.000)

Table 3.2 Descriptive statistics of the AScX index

AScX	
Number of observations	2608
Mean	0.000208
Standard deviation	0.010671
Skewness	-0.549
Kurtosis	5.472
Jarque-Bera test statistic	794.882205 (0.000)

Uncorrelated residuals

Following this condition there must be zero correlation between the different error terms, which excludes all forms of autocorrelation (Verbeek, 2008). According to the traditional finance theory, stock prices follow a random walk, meaning that there is no autocorrelation of the error terms. As shown in the literature review, stock market returns do not always follow a random walk. In case there is correlation between the error terms this results in similar problems to those of heteroskedasticity. Estimates of beta will be inefficient and the standard errors are estimated in the wrong way (Verbeek, 2008). The Durbin-Watson test is often performed to test for autocorrelation. However, due to the use of a lagged value of the dependent variable, which is either the AEX or AScX index, the Durbin Watson test cannot be used (Asteriou & Hall, 2011). Therefore, I perform the Breusch-Godfrey test, as this test accommodates for lagged values of the dependent variable. In case I find autocorrelation, I will correct for this by using Newey-West standard errors in the Ordinary Least Squares regression, since this is a heteroskedasticity and autocorrelation consistent (HAC) estimator.

Chapter 4

Results

In this section I will present the results of the different statistical methods to see if weather and biorhythm conditions have a significant effect on Dutch stock market returns. Also, I will show whether current mood determines to what extent an investor is influenced by weather and biorhythm.

4.1 Multi-collinearity and Gauss Markov results

Before running the OLS regression I will examine the results from various tests. From these tests I can conclude whether the conditions necessary for the OLS regression are met. First, I examine the value of the VIF and tolerance for the estimated models to check for the possible presence of multi-collinearity. The outcome can be found in Appendix A. Tolerance varies from 0.156 for sunshine to 0.997 for both the Monday dummy and AEX_{t-1}. As tolerance for the sunshine variable drops below 0.2, this is a cause for concern (Menard, 1995). An indicator of multi-collinearity is when correlations are above 0.8 or 0.9 between two predictor variables (Franke, 2010). The value of less than 0.2 for sunshine can be explained by the correlation matrix, which can also be found in Appendix A. The matrix shows a correlation coefficient of -0.854 between sunshine and cloud cover. This is not surprising, as when the sky is covered with more clouds, this means less hours of sunshine during a day. Problems can arise, as the contribution of both variables in explaining the dependent variable (daily change in AEX or AScX index returns) overlaps. The degree of contribution of cloud cover and sunshine individually is difficult to determine, which is conveyed in reduced regression coefficients and magnified standard errors (Tu, Kellett, Clerehugh, & Gilthorpe, 2005). To tackle this problem I made changes to the overall weather model as estimated in the Methodology section. This comes down to regressions which include either sunshine or cloud cover as weather variables. This makes sure that the beta coefficients do not suffer from multi-collinearity issues.

By examining fit lines on scatter plots created with Stata, I find linear relationships between all independent variables and the dependent variable. Due to the many data points, all scatterplots show clustered data around the regression line, as can be seen from the scatterplot in figure 4.1. None of the scatter plots show a curve in the data from which can be concluded that all relationships between the independent variable and dependent variable are linear. The linearity assumption is checked for both the AEX and AScX index by examining scatterplots. These scatterplots can be found in Appendix A.

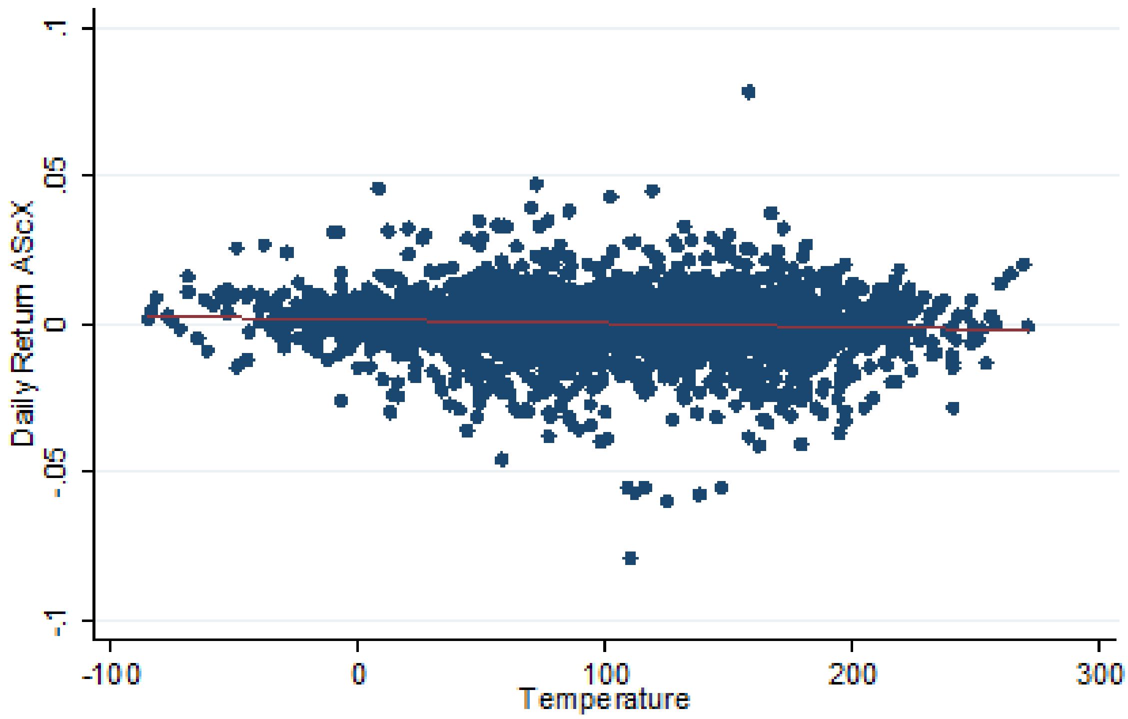

Fig. 4.1 Partial regression plot for the relationship between the AScX index and temperature. The value of 100 for temperature is equal to 10 degrees Celsius.

Additionally, the Augmented Dickey Fuller test demonstrates stationarity for both the daily returns of the AEX and AScX index, as the null hypothesis confirming a unit root can be rejected. The results of the Augmented Dickey Fuller test can be found in Appendix A.

I performed the Breusch-Pagan test to check for heteroskedasticity. The outcome of the Breusch-Pagan test for all tested regression analyses results in a significance level of 0.000, which can be found in Appendix A. This means that homoscedasticity is rejected and the OLS regression deals with heteroskedasticity. Therefore, all reported outcomes for the OLS regression will be run with Newey-West standard errors to correct for heteroskedasticity. Another reason why the Newey-West standard errors will be used is the presence of autocorrelation, as these standard errors are heteroskedasticity and autocorrelation consistent (Wooldridge, 2006). For all estimated regressions the chi-squared test statistic is significant, meaning that disturbances are serially correlated. Hence, Newey-West standard errors must be used (Asteriou & Hall, 2011). The output of the Breusch Godfrey test can also be found in Appendix A.

4.2 Expected outcome based on scatterplots

From the scatterplots and the betas of the fitted line, an expectation can be made about the answers to the sub questions resulting from the Literature Review. For all variables the relationship with the dependent variable is rather small. When rounded to a whole integer, all betas, except for the beta of the MSCI variable, result in zero. This makes it likely that the answers to Q1 and Q2, about the influence of weather and biorhythm variables on stock prices, will be that there is no effect. The regression analyses will show whether this expectation is correct.

4.3 Regression analysis

After performing the OLS with Newey-West standard errors[3] and the LAD, both analyses show similar results. Hence, reporting both regression analyses does not lead to new insights. Therefore, I only report the results of the LAD, as this is a more robust regression. The LAD involves both a robust estimation of the beta coefficients and the standard errors. In contrast, in the OLS only the Newey-West standard errors are robust to meet the Gauss Markov conditions (Ender, 2016). This means that the OLS is more sensitive to outliers, which may result in regression coefficients that show an inaccurate reflection of the underlying statistical relationship (IHS Global Inc., 2016).

[3]The Newey command that I used in Stata requires to choose the truncation parameter. To be a heteroskedasticity and autocorrelation-consistent (HAC) estimator, the truncation parameter must be large when using large samples, but much smaller than the number of observations. To determine this parameter, I used the rule of thumb developed by Stock and Watson (2011). The rule of thumb to determine the truncation parameter, called m, is dependent on the number of observations, T. The formula is m=$0.75T^{(1/3)}$ (Stock & Watson, 2011). In this study this results in a truncation parameter of 10 for the weather and biorhythm models and 8 for the mood models.

In tables 4.1 and 4.2 results of the Least Absolute Deviations regressions can be found for the estimated weather model. To correct for first order serial correlation, daily lagged returns of the dependent variable are added to each regression. In addition, the MSCI World Index is added to control for cross-country effects. These two control variables contribute to the explanatory power in all different setups of the regression. Both the AEX and AScX index are influenced by indices from other countries conveyed in the MSCI World Index and by Dutch stock market returns on the previous day. I tested the power of the control variables separately and together with the weather variables. When testing the significance of the weather variables, I take multi-collinearity issues of cloud cover and sunshine into account as discussed earlier in this chapter. This results in the setups shown in Tables 4.1 and 4.2.

The LAD regression does not show significant beta coefficients for the weather variables of interest at the 10%, 5% or 1% significance level when taking the AEX index as the dependent variable. When I take the AScX index as the dependent variable, the weather variable temperature does show significance at the 1% level in all setups.

Table 4.3 and Table 4.4 present the results of the Least Absolute Deviation regressions for the estimated biorhythm model. Beside the influence of weather mood-proxy variables, also biorhythm variables are of interest in this thesis. To test whether Seasonal Affective Disorder (SAD) and Daylight Saving Time Changes (DSTC) influence Dutch stock market returns significantly, the same approach has been used as in the weather model. The same control variables have been used to correct for first order serial correlation and cross-country effects. Similar to the weather model, returns of the previous day and returns of indices conveyed in the MSCI World Index show a significant relationship with both the AEX and AScX index.

As shown in the tables, I tested the estimated biorhythm model from the methodology section. When the AEX is used as dependent variable none of the biorhythm variables shows a significant relationship. For the AScX index the results are different. In the estimated biorhythm model only SAD is significant at the 5% level.

Lastly, the results of the LAD for the mood model can be found in Tables 4.5 to 4.8, results of the OLS with Newey-West standard errors can be found in Appendix B. I ran these tests to examine the potential effect of the previously defined mood-proxy variables on either a good mood or bad mood. I use the same approach as Dowling and Lucey (2005) who argue that mood is a result of historical stock returns. Therefore, when the short-run (10-day) moving average is above the long-run (200-day) moving average, investors are in a good mood and vice versa. This results in two data sets, in which we can speak of a good mood on 1262 days when using AEX daily returns as the dependent variable and 1300 days when using AScX daily returns as the dependent variable. Thus, investors are in a bad mood on 1147 days according to the AEX index and on 1109 days according to the AScX index. This is the first regression analysis that results in significant beta coefficients when the AEX index is taken as the dependent variable. Contrary to findings of the weather model, cloud cover and temperature show significant beta coefficients in the LAD when investors are in a good mood. However, when the AScX index is taken as the dependent variable, weather and biorhythm variables do not result in a significant relationship with either a bad or good mood.

The January effect is not present in the Dutch stock market. Both indices do not show significant results on the January variable. Although for most regressions the Monday variable presents a significant beta coefficient, this is against expectations of past literature. The Monday effect means that there is a decline in stock prices after the weekend, however none of the regression coefficients has a negative prefix. However, the effect is rather small as they are close to zero. This means there is almost no relationship between a Monday and the return on that day.

Table 4.1 This table shows the results of the Least Absolute Deviations regression, which tests the influence of various weather variables on the percentage change of daily returns of the AEX index between 1 January 2006 and 31 December 2015. The values in the table are the betas followed by either *, ** or *** which means significance at the 10%, 5% or 1% level respectively. When a cell is left blank, this means that the variable is not included in the regression analysis.

AEX			
Constant	-.000*	-.001	-.001
Monday Dummy	.001*	0.001*	0.001*
January Dummy	0.000	0.000	0.000
Return AEX_{t-1}	-.047***	-.048***	-.048***
Return $MSCI_t$	1.032***	1.031***	1.032***
Sunshine		-0.000	
Humidity		0.000	0.000
Temperature		0.000	0.000
Cloud Cover			-0.000
Pseudo R^2	.3980	.3983	.3983

Table 4.2 This table shows the results of the Least Absolute Deviations regression, which tests the influence of various weather variables on the percentage change of daily returns of the AScX index between 1 January 2006 and 31 December 2015. The values in the table are the betas followed by either *, ** or *** which means significance at the 10%, 5% or 1% level respectively. When a cell is left blank, this means that the variable is not included in the regression analysis.

AScX			
Constant	.000	.000	.001
Monday Dummy	.001*	.001*	.001
January Dummy	.001	.000	.000
Return $AScX_{t-1}$	.072***	.074***	.076***
Return $MSCI_t$	.629***	.632***	.634***
Sunshine		.000	
Humidity		.000	.000
Temperature		-.000**	-.000**
Cloud Cover			.000
Pseudo R^2	.2330	.2341	.2342

Table 4.3 This table shows the results of the Least Absolute Deviations regression, which tests the influence of biorhythm variables on the percentage change of daily returns of the AEX index between 1 January 2006 and 31 December 2015. The values in the table are the betas followed by either *, ** or *** which means significance at the 10%, 5% or 1% level respectively.

AEX	
Constant	.000
Monday Dummy	0.001*
January Dummy	0.000
Return AEX_{t-1}	-.048***
Return $MSCI_t$	1.035***
SAD	-.000
DSTC	-.002
Pseudo R^2	.3983

Table 4.4 This table shows the results of the Least Absolute Deviations regression, which tests the influence of biorhythm variables on the percentage change of daily returns of the AScX index between 1 January 2006 and 31 December 2015. The values in the table are the betas followed by either *, ** or *** which means significance at the 10%, 5% or 1% level respectively.

AScX	
Constant	-.001**
Monday Dummy	.001
January Dummy	.000
Return $AScX_{t-1}$	.079***
Return $MSCI_t$	.635***
SAD	.000**
DSTC	.002
Pseudo R^2	.2345

Table 4.5 This table shows the results of the Least Absolute Deviations regression, which tests the influence of various weather and biorhythm variables on investor mood between 1 January 2006 and 31 December 2015. The values in the table are the betas followed by either *, ** or *** which means significance at the 10%, 5% or 1% level respectively. The dependent variable takes the daily percentage change in closing value of the AEX when the short-run (10-day) moving average is above the long-run (200-day) moving average, which indicates a good mood. Otherwise it takes the value of zero. When a cell is left blank, this means that the variable is not included in the regression analysis.

AEX		
Constant	.002	-.001
Monday Dummy	-.000	-.000
January Dummy	-.001	-.001
Return AEX_{t-1}	-.069***	-.075***
Return $MSCI_t$	1.011***	1.010***
Sunshine	-.000	
Humidity	-.000	-.000
Temperature	.000	.000*
Cloud Cover		.000*
SAD	.000	.000
DSTC	-.003	-.003
Pseudo R^2	.3652	.3657

Table 4.6 This table shows the results of the Least Absolute Deviations regression, which tests the influence of various weather and biorhythm variables on investor mood between 1 January 2006 and 31 December 2015. The values in the table are the betas followed by either *, ** or *** which means significance at the 10%, 5% or 1% level respectively. The dependent variable takes the daily percentage change in closing value of the AScX when the short-run (10-day) moving average is above the long-run (200-day) moving average, which indicates a good mood. Otherwise it takes the value of zero. When a cell is left blank, this means that the variable is not included in the regression analysis.

AScX		
Constant	.002	-.002
Monday Dummy	.001**	.001**
January Dummy	-.000	-.000
Return AScX$_{t-1}$	0.039	.037
Return MSCI$_t$	.529***	.527***
Sunshine	-.000	
Humidity	.000	.000
Temperature	-.000	-.000
Cloud Cover		.000
SAD	-.000	-.000
DSTC	-.000	-.000
Pseudo R^2	.1739	.1739

Table 4.7 This table shows the results of the Least Absolute Deviations regression, which tests the influence of various weather and biorhythm variables on investor mood between 1 January 2006 and 31 December 2015. The values in the table are the betas followed by either *, ** or *** which means significance at the 10%, 5% or 1% level respectively. The dependent variable takes the daily percentage change in closing value of the AEX when the short-run (10-day) moving average is below the long-run (200-day) moving average, which indicates a bad mood. Otherwise it takes the value of zero. When a cell is left blank, this means that the variable is not included in the regression analysis.

AEX		
Constant	-.002	-.000
Monday Dummy	.001	.001**
January Dummy	.002*	.001
Return AEX_{t-1}	-.052***	-.052***
Return $MSCI_t$	1.027***	1.028***
Sunshine	.000	
Humidity	.000	.000
Temperature	-.000	-.000
Cloud Cover		-.000*
SAD	-.000	-.000
DSTC	.000	.004
Pseudo R^2	.4287	.4290

Table 4.8 This table shows the results of the Least Absolute Deviations regression, which tests the influence of various weather and biorhythm variables on investor mood between 1 January 2006 and 31 December 2015. The values in the table are the betas followed by either *, ** or *** which means significance at the 10%, 5% or 1% level respectively. The dependent variable takes the daily percentage change in closing value of the AScX when the short-run (10-day) moving average is below the long-run (200-day) moving average, which indicates a bad mood. Otherwise it takes the value of zero. When a cell is left blank, this means that the variable is not included in the regression analysis.

AScX		
Constant	.002	.001
Monday Dummy	-.000	-.000
January Dummy	-.001	.002
Return AScX$_{t-1}$	.079***	.080***
Return MSCI$_t$	.682***	.683***
Sunshine	-.000	
Humidity	-.000	-.000
Temperature	-.000	-.000
Cloud Cover		.000
SAD	.000	.000
DSTC	.002	.003
Pseudo R^2	.2681	.2680

Chapter 5

Discussion

In this section the results will be discussed for the weather model, biorhythm model and mood model. These results are compared to previous studies. Also, based on the outcome of the regressions, the sub questions to investigate whether various weather and biorhythm conditions are significantly correlated with daily returns of the AEX and AScX index can be answered. Also, I draw a conclusion on the potential influence that weather and biorhythm conditions have on investor mood.

5.1 Weather model

Monday and January effect

Although the Monday variable shows a significant beta coefficient in several setups in the LAD, the beta is near zero. This means there is almost no relationship between a Monday and the stock market return on that day. This result contradicts existing studies, which show a significant negative return on Mondays compared to other days of the week (Kamara, 1997; French, 1980; Wang, Li, & Erickson, 1997). This can be explained by the presence of many institutional investors who trade in stocks listed on the AEX index. Foreign bodies, which are mainly institutional investors, together with Dutch institutional investors hold 84% of the shares listed on the AEX index (Eumedion, 2014) and snap up the opportunity of the Monday effect (Kamara, 1997). This could have made the anomaly disappear. It is also possible that the Monday effect was never present in the Dutch stock market. This would imply that we cannot speak of a market-wide Monday effect.

Another insight provided by Kamara (1997) is that the Monday effect declines when trading costs decrease (Kamara, 1997). This can be explained, as lower transaction costs stimulate

Monday effect driven trading. As small-cap stocks often cope with high transaction costs, I expected to find a negative beta coefficient for the effect of Mondays on the AScX index. However, the regression coefficients do not contain a negative prefix and are close to zero. I think this can be explained by the large amount of literature in this field of interest. Informed investors participate in the stock market. When all investors are aware of the influence of a Monday on stock market returns, investors can account for this effect.

Also, the January effect is not present following the results, as there is no significant positive relationship between stock market returns for both indices and the month January. The results for the AEX are in line with research conducted by Thaler (1987) who also did not find abnormal returns in January for indices composed of primarily large firms like in the AEX index. Not finding the January effect for large-cap stocks can be explained by the proportion of individual versus institutional investors. Institutional investors are mainly trading in stocks listed on the AEX index, whereas individual investors hold small-cap stocks more often. Contrary to institutional investors, individual investors sell their stocks for tax reasons in December, such that they can claim a capital loss. They reinvest the money in January, which leads to rising stock prices, resulting in the January effect.

Against my expectations, the January effect is not found for small-cap stocks listed on the AScX index either. This might be explained by sophisticated investors who anticipate this anomaly, as the January effect has been discussed in many papers since the introduction of the effect by Wachtel (1942) (Malkiel, 2003). This can be explained by means of an example: In case stock prices are supposed to go up in the first week of January, investors will buy stocks on the last day of December and sell them in the first week of January. When many investors mimic this approach, they will start buying in the last week of December and will sell early in the first week of January. Thus, to profit from the January effect investors will start buying earlier in December, but will also sell earlier in January. Eventually, the January effect will self-destruct, as it is arbitraged away (Malkiel, 2003).

Barberis and Thaler (2003) refute this argument, as they argue that learning about the mispricing might be costly. However, I think this argument does not apply to the January effect, due to free accessible studies on this topic. Barberis and Thaler (2003) also argue that exploiting the mispricing can be risky. Since many researchers have demonstrated the existence of the January effect, exploiting the mispricing is not likely to be qualified as risky.

Influence of the weather

The results of the LAD for the weather models with the AEX index as the dependent variable show that no weather mood proxy variable influences Dutch stock market returns significantly. Due to multicollinearity issues, I tested sunshine and cloud cover in distinct regressions. However, this did not result in the regression coefficients being significant.

The significance of the relationship between hours of sunshine and stock market returns was previously found in many of the twenty-six countries studied by Hirshleifer and Shumway (2003). Sunshine does not have a significant influence on AEX and AScX index returns, which is similar to the finding of Pardo and Valor (2003) who also did not find a significant effect for hours of sunshine on Spanish stock market returns. The difference in results of the study conducted by Hirshleifer and Shumway (2003) and this research might be due to the different time frame in which the relationship is tested. Hirshleifer and Shumway (2003) used data between 1982 and 1997, whereas in this study data between 2006 and 2016 is used. Also, the location where the influence of hours of sunshine is measured differs in this study compared to the one of Hirshleifer and Shumway (2003). As this study is conducted more recently, it might be the case that investors were informed about the effect of sunshine on stock market returns and as a result the effect has disappeared.

Similar to hours of sunshine, other weather variables have no significant influence on the AEX index either. When looking at humidity, Krämer and Runde (1997) did not find a significant effect on German stock returns as well. Also in Spain, humidity did not lead to a significant relationship with Spanish stock market returns (Pardo & Valor, 2003). Hence, insignificant results for humidity on returns of the AEX and AscX index are not surprising. Humidity does not have a significant influence on Dutch stock market returns. Therefore, the answer to Q1.2 is that there is no significant relationship between humidity and daily returns of the AEX and AScX index.

Saunders (1993) did find a significant effect for cloud cover on stock market returns in the United States. However, cloud cover and stock market returns did not lead to a significant relationship in the United States in the research conducted by Trombley (1997). Also, Krämer and Runde (1997) did not find a relationship in Germany. In line with Trombley (1997) and Krämer and Runde (1997), cloud cover also did not show a significant relationship with daily returns of the AEX and AScX index. With these results Q1.3, which questions the influence of cloud cover on Dutch stock market returns, can be answered with a no. The difference between Krämer and Runde's (1997) and Saunders' (1993) results, can be explained by the way that the weather variable is specified (Krämer & Runde, 1997). Krämer and Runde (1997) show that good weather can both have bad and good stock market returns depending on the way in which the weather variable is defined. Therefore, Saunders' (1993) results might suffer from a Type I error. Trombley (1997) argues that the reason for finding a significant relationship is dependent on which data is being compared. This might be the reason for finding different results in the Dutch stock market compared to Saunders' (1993) findings in the United States.

I found a significant effect for temperature on returns of the AScX index in all tested setups. I expected this outcome, as research conducted by Cao and Wei (2005) also found significant effects in eight different financial markets. Additionally, Floros (2011) who examined the same relationship in Portugal presented similar results. Both found higher stock market returns when temperature was lower. This negative relationship is confirmed in the Netherlands in case the AScX index is taken as the dependent variable, as can be concluded from the negative prefix. Cao and Wei (2005) explain the negative relationship by aggression of investors. Lower temperatures can cause aggression leading to more risk-taking, whereas higher temperatures lead to apathy. The answer to Q1.1, which questions the relationship between temperature and Dutch stock market returns, is that there is only a significant relationship present when the AScX index is taken as dependent variable. The difference between results of the AEX and AScX index can be explained by a higher number of institutional investors trading in large-cap stocks listed on the AEX index. It indicates more rational behaviour of the AEX index, as investor sentiment has a stronger effect on small stocks, which are listed on the AScX index (Baker & Wurgler, 2006). Hence, institutional investors are not sensitive to temperature and its influence on stock market returns.

In the LAD regression, I reported the pseudo R-squared to measure the fit of the model. The pseudo R-squared compares the value of the likelihood of the estimated model to the value of the likelihood in case none of the explanatory variables are included in the regression (Stock & Watson, 2011). The interpretation of the pseudo R-squared is equal to the conventional R-squared (Isengildina, Irwin, & Good, 2008). As the values of the pseudo R-squared are similar for the different setups, I have not excluded setups based on the value of the pseudo R-squared. One thing to notice is that the values are quite low. As I try to find the impact of weather on human behaviour, a low r-squared is not surprising as human behaviour is hard to predict.

In Appendix B, all OLS regressions with Newey-West standard errors are accompanied with the F-value and its associated p-value, which helps to determine the joint significance of the regression (Heij, Boer, Franses, Kloek, & Dijk, 2004). As all p-values are 0.000, the null hypothesis, which states that the fit of the intercept model and the estimated weather model are equal, can be rejected in all tested setups.

5.2 Biorhythm model

Evidence from previous research led to the formulation of Q2. However, contrary to significant findings of Kamstra, Kramer and Levi (2000) in eight countries spread over both the Southern and Northern hemisphere, SAD does not significantly influence the AEX index in the Netherlands. Kamstra, Kramer and Levi (2000) showed that for most countries studied, the results are more significant when located at latitudes further from the equator. Following this reasoning, significant results are expected, as de Bilt is located 5790 kilometers from the equator (Beacom, 2016), resulting in clear seasonal variation in the Netherlands. Although a significant regression coefficient is not found for regressions with the AEX index as dependent variable, SAD has a significant effect on the returns of the AScX index. Although the correlation is rather small, as when rounded to three decimals the beta is zero, the relationship is positive. The positive relationship is similar to previous findings. This difference in results between the AEX and AScX index can be derived from research that shows that investor sentiment affects small-cap stocks more strongly (Baker & Wurgler, 2006). Again, this is caused by the type of investors that keep small-cap stocks, which are often individual investors instead of institutional investors (Lee, Shleifer, & Thaler, 1991). The other biorhythm variable in the estimated model is DSTC. Contrary to findings of Kamstra, Kramer and Levi (2000), a change in time of one hour forward in Spring and one hour backward in Autumn does not lead to a significant relationship with returns of the AScX or AEX index. The reason for a negative return after a one-hour time change might be caused through anxiety, resulting in a preference for safer investments. This can push down stock prices (Kamstra, Kramer, & Levi, 2000). From the results of the LAD regression, it seems that DSTC in the Netherlands does not lead to a level of anxiety that significantly influences Dutch stock market returns.

5.3 Mood model

I formed Q3 based on the difference in information processing when being in either a bad or good mood. When people are in a good mood, information is less critically processed compared to when people are in a bad mood (Schwarz, 1990). This means that people in a bad mood are more rational.

Results of the LAD regression indicate that there are no significant mood-proxy variables when investors are in a bad mood following AScX index returns, which is in line with my expectations based on research conducted by Schwarz (1990). For AEX Index returns, only a significant regression coefficient for cloud cover is found at the 10% level. When looking at investors in a good mood, again the LAD does not show significant mood-proxy variables for the AScX index, but when AEX is used as the dependent variable, both temperature and cloud cover show significance at the 10% level when the estimated model is tested. These results indicate that when investors are in a good mood, they are more easily influenced by weather conditions compared to when they are in a bad mood.

Overall, these results are against the expectations of Q3. Although the number of significant mood-proxy variables is greater for investors in a good mood compared to investors in a bad mood, this difference is rather small. Also, when investors are in a bad mood, irrelevant external factors such as the weather have a significant relationship with stock returns, which is not only the case for investors in a good mood. Schwarz's (1990) conclusion on processing information more critically when being in a bad mood might still be valid, however it could be the case that weather and biorhythm influence investor decisions subconsciously. Q3, which questions whether investors are more easily affected by mood-proxy variables when being in a good mood, must be answered with no. As both types of mood give significant results for the weather variables, it is likely that investors are influenced by incorrect judgements, because of misattribution of arousal. Since not all weather variables give significant results and the weather variables that are significant are close to zero, further research should investigate to what extent investors suffer from misattribution of arousal, which might indicate that the Dutch stock market is not fully efficient.

It is remarkable that only for investors who trade in stocks on the AEX index good and bad mood have a significant relationship with weather variables. This is unexpected, since previous findings in the Dutch stock market imply that investors active in stocks listed on the AScX index are more sensitive to the weather and biorhythm changes compared to investors who participate in trading in stocks listed on the AEX index. Therefore, the definition of good and bad mood by using the short-run moving average in comparison to the long-run moving average might not be a good indicator of mood for both types of indices. Dowling and Lucey (2005) found that investors in a good mood are more easily influenced by the weather, which was expected. However, they did not test whether the definition also applies to small-cap indices. Regarding my findings in the Dutch stock market, further research should examine whether past stock market returns give a good indication of mood for investors active in small-cap indices, as my results imply that weather and biorhythm variables do not have a significant relationship with current mood for traders active on the AScX index.

Chapter 6

Implications

In my research, I do not find a market wide effect for the influence of weather and biorhythm variables on Dutch stock market returns. As weather and biorhythm variables do not show significant results for the AEX index, a trading strategy based on these factors would not lead to earning excess returns. For the AEX index on which large-cap stocks are listed, I cannot reject the efficient market hypothesis for the semi-strong and strong form. These results are in line with previous research conducted by Pardo and Valor (2003), Krämer and Runde (1997) and Trombley (1997), who also did not find significant results in other countries on the influence of the weather on stock market returns. I expand their research by confirming their findings in another market and in a more recent time frame. Due to lower transaction costs for large-cap stocks compared to small-cap stocks (Kamara, 1997), it is likely that institutional investors already snapped up the opportunity of earning excess returns by adopting a weather or biorhythm based portfolio. Therefore, the anomaly might have disappeared as sophisticated investors on the AEX index anticipated this phenomenon.

The results of the AScX imply that considering weather and biorhythm variables in an investment strategy can result in a higher payoff. A significant effect of weather variables on stock market returns was also found in other studies (Cao & Wei, 2005; Floros, 2011; Saunders, 1993). Therefore, the result that the weather influences investor mood and thus their behaviour is not surprising. From a theoretical perspective, these results imply a violation of the efficient market hypothesis in the semi-strong and strong form, as temperature and SAD show significant beta coefficients for the AScX index. These effects of investor sentiment on stock market behaviour can be explained by the two building blocks of behavioural finance: Limits to arbitrage and psychology (Barberis & Thaler, 2003). Limits to arbitrage is present, as it is likely that rational agents do not correct for other irrational investors, due to high transaction costs for small-cap stocks and uncertainty of weather forecasts. Psychology is about systematic biases when making decisions. The misattribution bias applies here, as investors are influenced by temperature and seasonal affective disorder, which have no direct relationship with stock market returns. They attribute the experienced feeling to the wrong cause (Ross, 1977). However, this only applies to investors active in stocks listed on the AScX index. An investment strategy considering the weather and biorhythm does not lead to a higher payoff for investors who trade in stocks listed on the AEX index.

Additionally, I can draw conclusions on a potential trading strategy for the AScX index based on my results. At first glance, trading based on the weather and biorhythm can be beneficial. However, weather conditions and biorhythm change all the time. Trading on these events entails frequent trading. As small-cap stocks are listed on the AScX index, this brings along higher transaction costs compared to the AEX index where large-cap stocks are listed (Kamara, 1997). When taking transaction costs into account, it is questionable whether trading based on these factors are still feasible. Kamstra, Kramer and Levi (2003) show that a portfolio based on the SAD effect can lead to excess returns when not taking transaction costs into account. When investing in stocks listed on a stock exchange in the Northern Hemisphere's fall and winter and thereafter moving to the Soutern Hemisphere's fall and winter can result in an annual return of 21.1 percent instead of 13.2 percent when adopting a neutral strategy. This is because stock market returns decrease during the fall, as the amount of daylight is diminishing and people suffer from the winterblues. When investing in this period, investors can buy stocks at low prices. The stock prices will go up after the winter stolstice when the amount of daylight during a day increases. Selling after the winter stolstice therefore results in a higher payoff.

However, Kamstra, Kramer and Levi (2003) do not take transaction costs into account, which plays an important role when investing in stocks listed on the Dutch AScX index.

It is important for investors to realize that it asks for a significant amount of effort to adopt a weather or biorhythm based strategy, as weather predictions are known at short notice and can be uncertain. Also, the influence of temperature and SAD is significant but rather small, as the beta coefficient is close to zero. However, the aim of this thesis is to research if there is a relationship between investor sentiment and Dutch stock market returns, instead of making suggestions for a trading strategy.

Additionally, from the insight that temperature has a significant effect on AScX index returns, a practical implication can be derived. When companies with market caps less than 2 billion, which classify as small market capitalizations (Financial Engines, 2016), are planning an Initial Public Offering (IPO) it might be profitable to take the weather into account. As there is a negative relationship between small-cap stocks and temperature, an IPO on days with a low temperature can result in a rapid increase of stock prices. This can be explained by aggression due to the low temperature outside leading to more risk-taking behaviour (Cao & Wei, 2005).

Lastly, in my research mood is measured as a result of past stock market performance, which leads to a similar outcome for bad and good mood. Although there is a difference in the way information is processed when being in either a good or bad mood, the influence of weather and biorhythm variables is comparable for both mood states. The expectation that investors in a good mood were more easily influenced by weather and biorhythm variables cannot be verified based on my results. The practical implication is that when investors compose a portfolio based on the weather, examining the long run moving average versus the short run moving average to determine the current mood state, this does not lead to insights for a more profitable trading strategy for good mood compared to a bad mood.

Chapter 7

Conclusion

In this final section, I will draw conclusions on the research question as formulated in the Introduction. To do so, I will consider the statistical results and the practical and theoretical implications in the previous section. Thereafter, I will discuss the limitations of my research approach and will make suggestions for future research.

The aim of this master thesis is to draw a conclusion on the influence of investor mood on stock market returns in the Netherlands. According to the traditional finance theory, an investor is classified as a Homo Economicus (Mill, 1848). This means investors are rational and behave according to the expected utility theory when making decisions under risk and uncertainty. However, many studies have shown that investor sentiment plays a role in making financial decisions. This has been demonstrated based on several events, such as soccer matches and the number of hours of sunshine per day that significantly influence investor sentiment. In this thesis, weather and biorhythm variables have been taken as mood-proxy variables to study the influence on the AEX index and AScX index, which are two Dutch stock market indices.

Overall, I conclude that Dutch weather conditions do not significantly influence daily returns of the AEX index. The weather does not influence investors in such a way that they behave differently when buying and selling stocks on the AEX index. However, individual investors active in trading stocks listed on the AScX index are more easily influenced by the weather. Temperature does show a significant beta coefficient when measuring its influence on the AScX index. The result that weather has greater impact on the AScX compared to the AEX was expected, as research conducted by Baker & Wurgler (2006) showed that investor sentiment affects small-cap stocks more strongly. On the AEX Index, the most actively traded securities are listed, whereas the AScX index is composed of small-cap stocks. The type of investor is different for both indices. Individuals trade on the AScX index, contrary to institutional investors who trade on the AEX Index, which might be the cause of this outcome (Lee, Shleifer, & Thaler, 1991). From these results, I conclude that the AEX index confirms the efficient market hypothesis in the semi-strong form and strong form. However, traders participating on the AScX index are influenced by the weather variable temperature, which can be explained by behavioural finance due to limits to arbitrage and the misattribution bias. Although, the beta coefficient for temperature is rather small, the stock market for small-cap stocks cannot be qualified as fully rational.

For the biorhythm variable Seasonal Affective Disorder (SAD), similar results are found. SAD does not have a significant relationship with the AEX index, but SAD does have a significant influence on the returns of the AScX index. The positive relationship means that when there are more hours of daylight during a day, this leads to more risk taking. Following these results, behaviour of individual investors on the stock market is affected by the number of hours of daylight in a day, as they attribute the experienced feeling to the wrong cause. This results in irrationality when making investment decisions. The other biorhythm variable, Daylight Saving Time Change, does not have a significant relationship with either the AEX or AScX index. Dutch investors do not seem to cope with anxiety due to the time change, which could result in a decline in stock prices.

By means of these results, I conclude that the Dutch stock market for large-cap stocks behaves in line with the efficient market hypothesis. For small-cap stocks, the insights are different, as temperature and SAD have a significant influence on stock market returns. Therefore, the small-cap stock market cannot be classified as fully rational. However, since the beta coefficients of temperature and SAD are close to zero, the influence is rather small.

Lastly, I researched to what extent there is a difference in the significance of weather and biorhythm variables when investors are in either a good or bad mood. Schwarz (1990) found that when people are in a good mood, information is less critically processed compared to when people are in a bad mood. From this research, I expected that investors in a good mood are more easily affected by the weather compared to when these investors are in a bad mood. For the AEX index I found significant weather variables in both mood states. Hence, for investors who trade in stocks on the AEX, the weather has a significant relationship with the current mood of investors, which implies that investors suffer from the misattribution bias. For the AScX index, weather and biorhythm conditions do not have a significant relationship with current mood. As this is against the overall finding that individual investors active on the AScX index are more sensitive to weather and biorhythm conditions further research must investigate whether the definition of mood in this paper is properly characterized for both large-cap and small-cap indices.

7.1 Limitations

7.1.1 Investor sentiment

In this thesis, I rely on research conducted by Howarth and Hoffman (1984) and Schwarz and Clore (1983) which showed that weather influences a person's mood. This finding has been expanded to also viewing biorhythm changes as a phenomenon that influences someone's mood. After these findings, many studies have used weather and biorhythm variables as mood variables to determine whether investor sentiment influences stock market returns. However, by relying on this past research construct validity, defined as the experimental demonstration that a study measures the phenomenon it declares to be measuring (Brown, 2000), might be lower. Measuring the effect of investor sentiment on Dutch stock market returns by using known moods would increase the validity of this study. Making inferences on the relationship between the weather and biorhythm and its influence on investor mood would no longer be necessary when knowing investor mood with certainty. In case mood is known in advance, the effect of weather and biorhythm variables on mood and thus on stock market returns could have been measured. I also measured this, but in my study mood is a derived variable of past stock market returns.

7.1.2 Including fewer weather variables

Previously conducted studies that draw conclusions on the potential relationship between the weather and stock market returns only tested one or two weather variables apart from the control variables (Cao & Wei, 2005; Floros, 2011; Hirshleifer & Shumway, 2003; Pardo & Valor, 2003; Saunders, 1993; Trombley, 1997). In this thesis, I tested four weather variables: sunshine, temperature, cloud cover and humidity. As in the past all these weather variables have been studied in different markets and during different time frames, I am interested in testing all these weather variables to get a clear view which variables influence the Dutch stock market. By testing many variables at the same time, the risk for multi-collinearity issues increases. Testing these variables separately together with the control variables might lead to more similar results as in past literature.

7.1.3 Location of measured weather variables

Geographic diffusion might have decreased the explanatory power of this study. The weather has been measured in de Bilt, which is a small town in the middle of the Netherlands. However, investors active on the AEX and AScX are spread across the country and are not only citizens of de Bilt. It is likely that the impact of this measurement is rather small, due to the size of the Netherlands. Investors are spread across a relatively small area, which makes big differences in weather conditions unlikely. Biorhythm is not associated with a specific city or location. So for the results on biorhythm this limitation does not apply.

7.1.4 Multiple significance testing

In my research, there is a risk for multiple significance testing. When drawing conclusions on the tested relationship, looking at significance for several individual comparisons may result in an excessive rate of type I errors, also known as a false positive conclusion (Hochberg & Benjamin, 1990). In practice this means that when testing at a 5% significance level, when performing twenty tests there is a 64%[4] chance of finding at least one significant result by chance (Bland & Douglas, 1995). I did not adopt the remedy for this potential problem, which is called the Bonferroni correction, as it is often seen as too conservative (Hochberg & Benjamin, 1990). However, when adopting this procedure, it increases the power of the test, as the region of acceptance is reduced.

7.2 Recommendations for future research

By writing this thesis, I can draw a conclusion on the influence of weather and biorhythm variables on investors active in the Dutch stock market. However, based on this study I encourage further research on this topic.

First, mood is hard to measure, as observing people does not lead to reliable conclusions on their current mood. In this research, I used the weather and biorhythm as mood proxy variables. However, the effect of these variables on mood relies on generalizing findings of past research to Dutch investors. The influence of mood variables is still ambiguous. Also, it is questionable whether a type of behaviour that is associated with a certain mood can be generalized to all investors. When being in a bad mood, information is processed more critically compared to when people are in a good mood (Schwarz, 1990). However, it is likely that this does not apply to all people. Some investors may become more aggressive

[4] $P_{\text{at least one significant result}} = 1 - P_{\text{no significant results}} = 1 - (1 - 0.05)^{20}$

due to their bad mood, leading to more risk-taking behaviour. The aim of future research should be to develop a model that gives certainty about a person's mood based on influential factors. In case a significant relationship between mood, classified as investor sentiment in finance, and stock market returns will be found, people active in financial markets should consider mood states in the asset-pricing model.

Additionally, when we know the determinants of investor mood, investors can be made aware of the effect these factors have on their state of mind and on their investment behaviour. The influence of mood is irrelevant for their investment decisions and may be overcome by educating investors about the consequences.

Another recommendation for future research is to measure other weather variables such as precipitation, wind speed and snowfall. By increasing the scope of this research a more complete picture can be drawn on which weather conditions influence investors trading behaviour.

Also, a specific answer to the question why different results are found compared to existing literature can be provided. These answers must be based on hypotheses that can or cannot be rejected in further research. In my research, I find results in line with previously conducted studies, but also results contradictory to existing studies. I explain these differences based on adopting explanations derived from existing literature. For example, not finding the January and Monday effect might be due to the amount of publications on these anomalies. Also, finding an effect for temperature on returns of the AScX, but not finding this effect for AEX returns might be due to the difference in type of investors. However, in further research I recommend to test hypotheses about plausible reasons for specific results and test whether these explanations are valid in the market that is being researched.

Lastly, due to the different findings in previous studies on the effect of hours of sunshine on stock market returns and my research, future research could demonstrate whether this effect is different for various time frames. This could lead to valuable insights for investors, especially due to the developments of climate change causing global warming. In case sunshine effects are only associated with specific time frames, meaning that investors adapt to changes in the weather, this is important when choosing a trading strategy. In case the effect of sunshine on stock returns will be found in all time frames, this is an important insight for profitable trading strategies, especially as weather conditions are likely to become more extreme (Shaftel, 2016).

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Appendix A

Data checks

Multi-collinearity check

Only results with the AEX index as the dependent variable are shown, as taking the AScX index as the dependent variable gives similar results.

Tolerance and VIF results

Table A.1 This table shows the values of the VIF and tolerance for the weather model.

	Tolerance	**VIF**
Monday Dummy	.997	1.003
January Dummy	.873	1.145
Return AEX_{t-1}	.997	1.003
Return $MSCI_t$	.995	1.006
Sunshine	.166	6.013
Humidity	.482	2.077
Temperature	.716	1.397
Cloud Cover	.242	4.135

Table A.2 This table shows the values of the VIF and tolerance for the biorhythm model.

	Tolerance	**VIF**
Monday Dummy	.969	1.033
January Dummy	.853	1.172
Return AEX_{t-1}	.997	1.003
Return $MSCI_t$	.995	1.005
SAD	.853	1.17
DSTC	.965	1.03

Table A.3 This table shows the values of the VIF and tolerance for the mood model

	Tolerance	**VIF**
Monday Dummy	.967	1.034
January Dummy	.841	1.189
Return AEX_{t-1}	.997	1.003
Return $MSCI_t$	.993	1.007
Sunshine	.156	6.415
Humidity	.451	2.216
Temperature	.459	2.179
Cloud Cover	.228	4.377
SAD	.346	2.889
DSTC	.964	1.037

Correlation matrix

Table A.4 This table shows the correlation coefficients of the explanatory and control variables used in the analysis. ** indicates significance at the 1% level.

	Monday Dummy	**January Dummy**	**Return AEX_{t-1}**	**Return $MSCI_t$**	**Sunshine**	**Humidity**	**Temperature**	**Cloud Cover**	**SAD**	**DSTC**
Monday Dummy	1	-.001	-.018	-.025	.030	-.018	-.002	-.014	.000	.176**
January Dummy	-.001	1	-.001	-.016	-.192**	.166**	-.348**	.096**	.382**	-.027
Return AEX_{t-1}	-.018	-.001	1	.048*	-.012	.012	-.010	-.001	.011	-.017
Return $MSCI_t$	-.025	-.016	.048*	1	-.015	.013	-.033	-.004	.010	-.040*
Sunshine	.030	-.192**	-.012	-.015	1	-.710**	.372**	-.854**	-.499**	.016
Humidity	-.018	.166**	.012	.013	-.710**	1	-.347**	.554**	.525**	-.009
Temperature	-.002	-.348**	-.010	-.033	.372**	-.347**	1	-.170**	-.728**	-.012
Cloud Cover	-.014	.096**	-.001	-.004	-.854**	.554**	-.170**	1	.252**	-.022
SAD	.000	.382**	.011	.010	-.499**	.525**	-.728**	.252**	1	.029
DSTC	.176**	-.027	-.017	-.040*	.016	-.009	-.012	-.022	.029	1

Two-way scatterplots of stock returns and explanatory variables

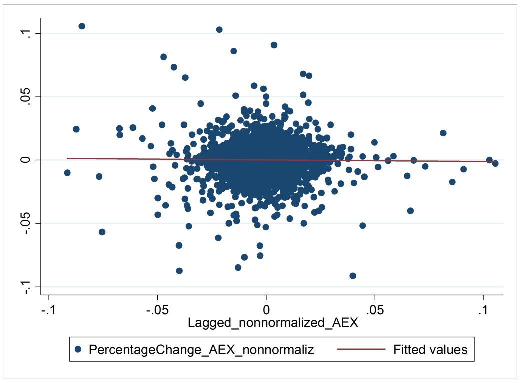

Fig. A.1 This figure shows the two-way scatterplot of daily AEX returns and the one day lagged return of the AEX.

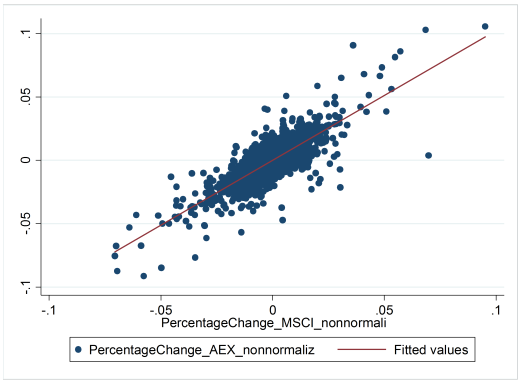

Fig. A.2 This figure shows the two-way scatterplot of daily AEX returns and the MSCI World Index.

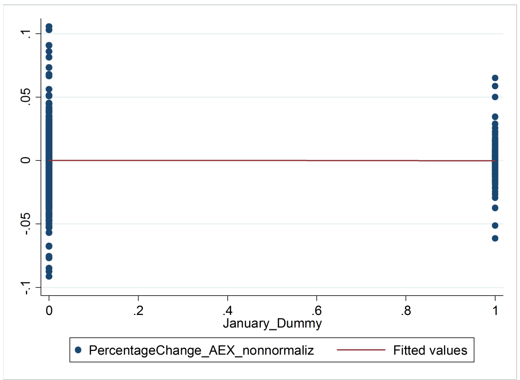

Fig. A.3 This figure shows the two-way scatterplot of daily AEX returns and the January dummy.

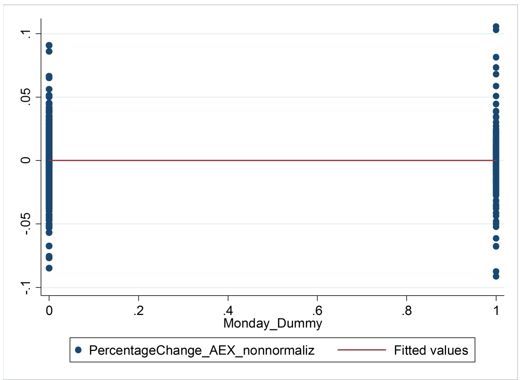

Fig. A.4 This figure shows the two-way scatterplot of daily AEX returns and the Monday dummy.

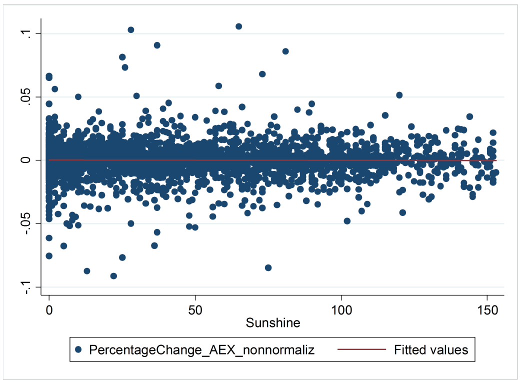

Fig. A.5 This figure shows the two-way scatterplot of daily AEX returns and Sunshine.

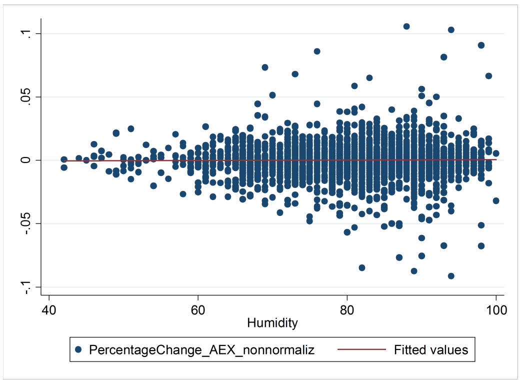

Fig. A.6 This figure shows the two-way scatterplot of daily AEX returns and Humidity.

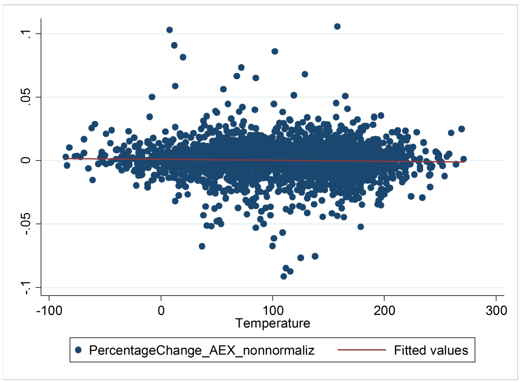

Fig. A.7 This figure shows the two-way scatterplot of daily AEX returns and Temperature.

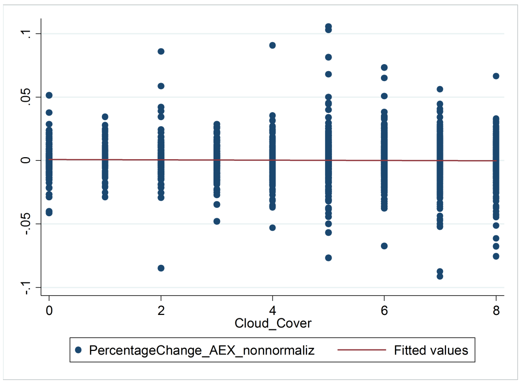

Fig. A.8 This figure shows the two-way scatterplot of daily AEX returns and Cloud Cover.

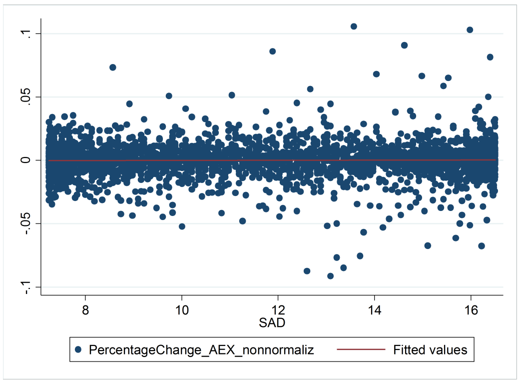

Fig. A.9 Two-way scatterplot of daily AEX returns and Seasonal Affective Disorder.

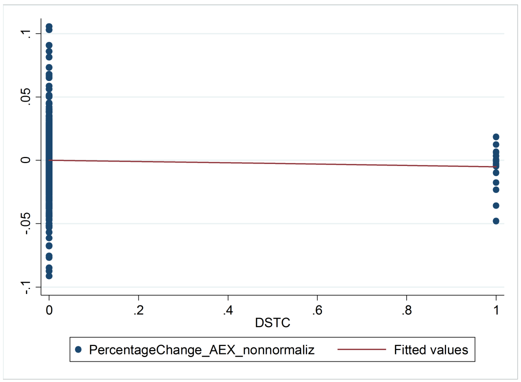

Fig. A.10 This figure shows the two-way scatterplot of daily AEX returns and Daylight Saving Time Changes.

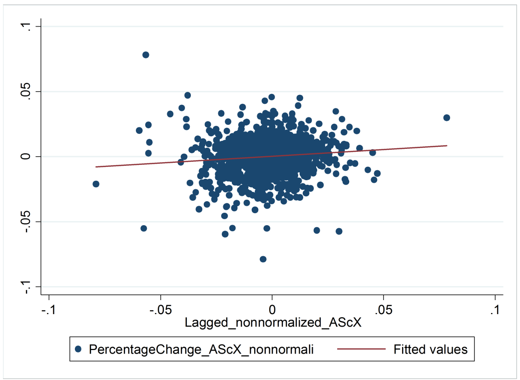

Fig. A.11 This figure shows the two-way scatterplot of daily AScX returns and one day lagged AScX returns.

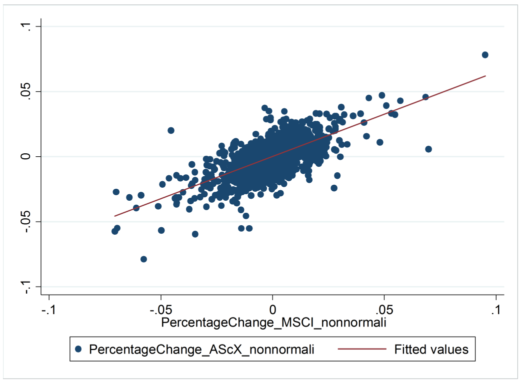

Fig. A.12 This figure shows the two-way scatterplot of daily AScX returns and the MSCI World Index.

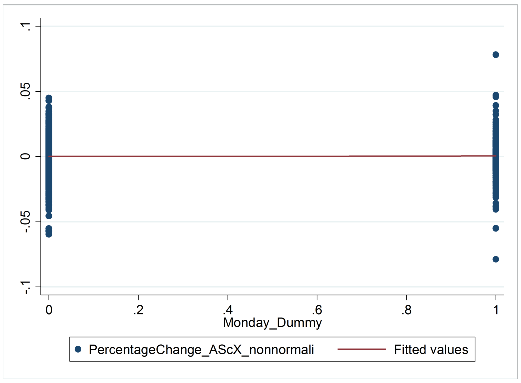

Fig. A.13 This figure shows the two-way scatterplot of daily AScX returns and the Monday dummy.

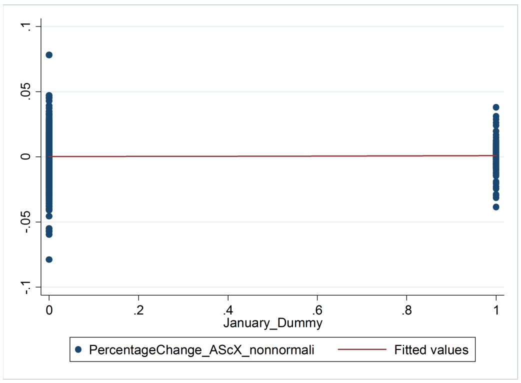

Fig. A.14 This figure shows the two-way scatterplot of daily AScX returns and the January dummy.

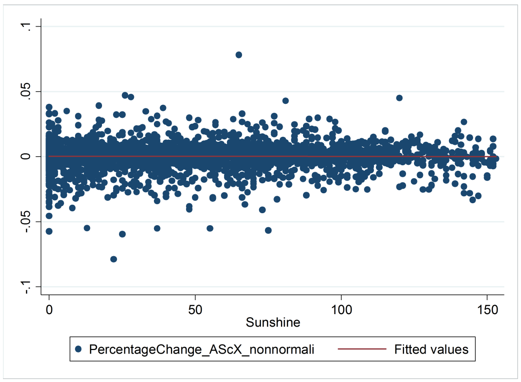

Fig. A.15 This figure shows the two-way scatterplot of daily AScX returns and Sunshine.

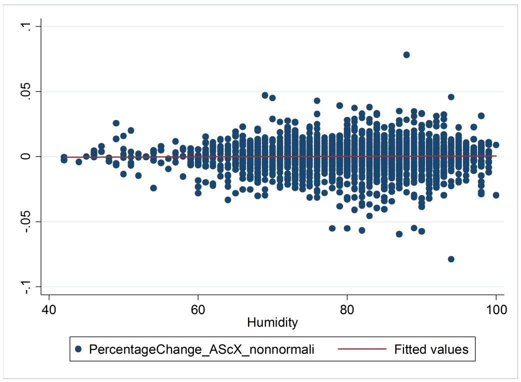

Fig. A.16 This figure shows the two-way scatterplot of daily AScX returns and Humidity.

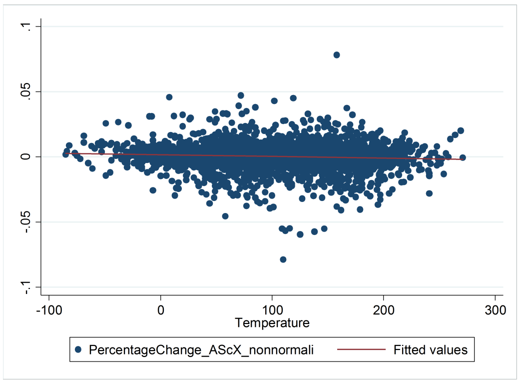

Fig. A.17 This figure shows the two-way scatterplot of daily AScX returns and Temperature.

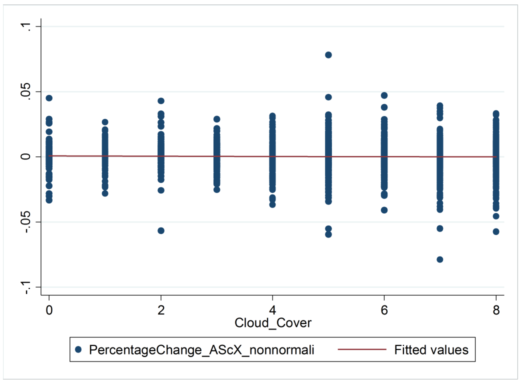

Fig. A.18 This figure shows the two-way scatterplot of daily AScX returns and Cloud Cover.

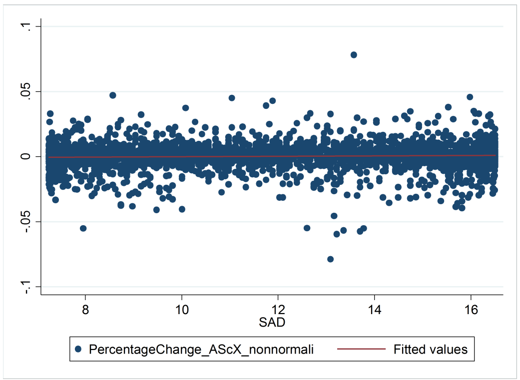

Fig. A.19 This figure shows the Two-way scatterplot of daily AScX returns and Seasonal Affective Disorder.

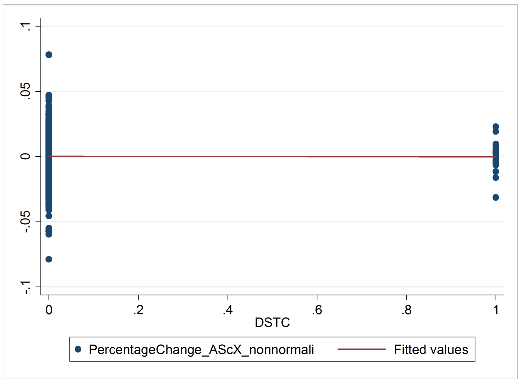

Fig. A.20 This figure shows the two-way scatterplot of daily AScX returns and Daylight Saving Time Changes.

Table A.5 This table shows the slope of the fitted lines of the two-way scatter plots that are depicted above. The coefficients give the correlation between the dependent variable, which is the daily return of the AEX index, and the weather and biorhythm variables.

AEX	
Return AEX_{t-1}	-.0135194
Return $MSCI_t$	1.022828
Monday	-.0000831
January	-.0002334
Sunshine	-0.00000197
Humidity	0.0000174
Temperature	-0.00000727
Cloud Cover	-0.0001012
SAD	.0000492
DSTC	-.0053573

Table A.6 This table shows the slope of the fitted lines of the two-way scatter plots that are depicted above. The coefficients give the correlation between the dependent variable, which is the daily return of the AScX index and the weather and biorhythm variables.

AScX	
Return $AScX_{t-1}$	.1037428
Return $MSCI_t$	.6503111
Monday	.0001982
January	.0006822
Sunshine	-0.00000149
Humidity	.0000162
Temperature	-.0000122
Cloud Cover	-.0001003
SAD	.0001466
DSTC	-.0003959

Augmented Dickey Fuller test

Table A.7 This table shows the results of the Augmented Dickey Fuller test, by using the dfuller command in Stata to check for stationarity. In the second column the results for the AEX index as dependent variables are shown and in the third column the results for the AScX index as dependent variable are presented.

Test for a unit root	**Daily return of the AEX**	**Daily return of the AScX**
Options	Constant, Trend	Constant, Trend
Test statistic	-51.729	-46.015
P-value	0.000	0.000
Critical values		
1%	-3.960	-3.960
5%	-3.410	-3.410
10%	-3.120	-3.120

Breusch-Pagan test

Table A.8 This table shows the outcome of the Breusch-Pagan test to check for heteroskedasticity, which is performed in Stata with the command 'hettest'. The AEX index is used as the dependent variable. When a cell contains an X this means that the variable is included in the regression analysis. The last row shows the Chi-squared test statistic from which can be concluded whether heteroskedasticity is present.

AEX percentage change												
Monday Dummy	X	X	X	X	X	X	X	X	X	X	X	X
January Dummy	X	X	X	X	X	X	X	X	X	X	X	X
Return AEX_{t-1}	X	X	X	X	X	X	X	X	X	X	X	X
Return $MSCI_t$	X	X	X	X	X	X	X	X	X	X	X	X
Sunshine		X		X		X		X			X	
Humidity			X	X		X		X			X	
Temperature					X	X		X			X	
Cloud Cover							X	X			X	
SAD									X	X	X	
DSTC										X	X	X
Chi-squared test statistic (p-value)	296.90 (0.000)	299.36 (0.000)	340.78 (0.000)	357.09 (0.000)	312.46 (0.00)	364.66 (0.000)	298.47 (0.000)	380.95 (0.000)	336.92 (0.000)	337.81 (0.000)	388.01 (0.000)	297.29 (0.000)

Table A.9 This table shows the outcome of the Breusch-Pagan test to check for heteroskedasticity, which is performed in Stata with the command ‘hettest’. The AScX index is used as the dependent variable. When a cell contains an X this means that the variable is included in the regression analysis. The last row shows the Chi-squared test statistic from which can be concluded whether heteroskedasticity is present.

AScX percentage change												
Monday Dummy	X	X	X	X	X	X	X	X	X	X	X	X
January Dummy	X	X	X	X	X	X	X	X	X	X	X	X
Return $AScX_{t-1}$	X	X	X	X	X	X	X	X	X	X	X	X
Return $MSCI_t$	X	X	X	X	X	X	X	X	X	X	X	X
Sunshine		X		X		X		X			X	
Humidity			X	X		X		X			X	
Temperature					X	X		X			X	
Cloud Cover							X	X			X	
SAD									X	X	X	
DSTC										X	X	X
Chi-squared test statistic (p-value)	275.74 (0.000)	275.71 (0.000)	292.32 (0.000)	295.04 (0.000)	278.55 (0.000)	295.08 (0.000)	273.28 (0.000)	300.52 (0.000)	284.91 (0.000)	286.35 (0.000)	303.46 (0.000)	276.80 (0.000)

Breusch-godfrey test

Table A.10 This table shows the outcome of the Breusch-Godfrey test to check for autocorrelation, which is performed in Stata with the command ‘estat bgodfrey’. The AEX index is used as the dependent variable. When a cell contains an X this means that the variable is included in the regression analysis. The last row shows the Chi-squared test statistic from which can be concluded if autocorrelation is present.

AEX percentage change												
Monday Dummy	X	X	X	X	X	X	X	X	X	X	X	X
January Dummy	X	X	X	X	X	X	X	X	X	X	X	X
Return AEX $_{t-1}$	X	X	X	X	X	X	X	X	X	X	X	X
Return $MSCI_t$	X	X	X	X	X	X	X	X	X	X	X	X
Sunshine		X		X		X		X			X	
Humidity			X	X		X		X			X	
Temperature					X	X		X			X	
Cloud Cover							X	X			X	
SAD									X	X	X	
DSTC										X	X	X
Chi-squared test statistic (p-value)	199.60 (.000)	199.04 (.000)	199.68 (.000)	199.11 (.000)	199.63 (.000)	199.02 (.000)	198.72 (.000)	199.54 (.000)	199.60 (.000)	199.85 (.000)	200.37 (.000)	199.86 (.000)

Table A.11 This table shows the outcome of the Breusch-Godfrey test to check for autocorrelation, which is performed in Stata with the command ‘estat bgodfrey’. The AScX index is used as the dependent variable. When a cell contains an X this means that the variable is included in the regression analysis. The last row shows the Chi-squared test statistic from which can be concluded if autocorrelation is present.

AScX percentage change												
Monday Dummy	X	X	X	X	X	X	X	X	X	X	X	X
January Dummy	X	X	X	X	X	X	X	X	X	X	X	X
Return $AScX_{t-1}$	X	X	X	X	X	X	X	X	X	X	X	X
Return $MSCI_t$	X	X	X	X	X	X	X	X	X	X	X	X
Sunshine		X		X		X		X			X	
Humidity			X	X		X		X			X	
Temperature					X	X		X			X	
Cloud Cover							X	X			X	
SAD									X	X	X	
DSTC										X	X	X
Chi-squared test statistic (p-value)	86.77 (0.000)	86.48 (0.000)	86.84 (0.000)	86.55 (0.000)	88.03 (0.000)	88.17 (0.000)	85.91 (0.000)	87.53 (0.000)	87.03 (0.000)	87.13 (0.000)	87.60 (0.000)	86.93 (0.000)

Appendix B

Statistical Analysis

Output Ordinary Least Squares regression analysis with Newey-West standard errors

Table B.1 This table shows the results of the Ordinary Least Squares regression with Newey-West standard errors, which tests the influence of various weather variables on the percentage change of daily returns of the AEX index between 1 January 2006 and 31 December 2015. The values in the table are the betas followed by either *, ** or *** which means significance at the 10%, 5% or 1% level respectively. When a cell is left blank, this means that the variable is not included in the regression analysis.

AEX			
Constant	-.000	-.002	-.001
Monday Dummy	.001	.001	0.001
January Dummy	.000	.000	.000
Return AEXt-1	-.052***	-.052***	-.053***
Return MSCIt	1.028***	1.027***	1.027***
Sunshine		0.000	
Humidity		0.000	0.000
Temperature		0.000	0.000
Cloud Cover			0.000
F-value (p-value)	539.69 (.000)	310.27 (.000)	308.81 (.000)

Table B.2 This table shows the results of the Ordinary Least Squares regression with Newey-West standard errors, which tests the influence of various weather variables on the percentage change of daily returns of the AScX index between 1 January 2006 and 31 December 2015. The values in the table are the betas followed by either *, ** or *** which means significance at the 10%, 5% or 1% level respectively. When a cell is left blank, this means that the variable is not included in the regression analysis.

AScX			
Constant	.000	-0.001	0.001
Monday Dummy	.001*	.001	.001
January Dummy	.001*	.001	.001
Return AScXt-1	.080***	.078***	.078***
Return MSCIt	.649***	.648***	.647***
Sunshine		.000*	
Humidity		.000	.000
Temperature		-.000***	-.000***
Cloud Cover			-.000*
F-value (p-value)	209.58 (.000)	118.70 (.000)	117.41 (.000)

Table B.3 This table shows the results of the Ordinary Least Squares regression with Newey-West standard errors, which tests the influence of biorhythm variables on the percentage change of daily returns of the AEX index between 1 January 2006 and 31 December 2015. The values in the table are the betas followed by either *, ** or *** which means significance at the 10%, 5% or 1% level respectively.

AEX	
Constant	-.000
Monday Dummy	.001
January Dummy	.000
Return AEX_{t-1}	-.053***
Return $MSCI_t$	1.027***
SAD	.000
DSTC	-.001
F-value (p-value)	359.06 (.000)

Table B.4 This table shows the results of the Ordinary Least Squares regression with Newey-West standard errors, which tests the influence of biorhythm variables on the percentage change of daily returns of the AScX index between 1 January 2006 and 31 December 2015. The values in the table are the betas followed by either *, ** or *** which means significance at the 10%, 5% or 1% level respectively.

AScX	
Constant	-.001**
Monday Dummy	.001
January Dummy	.001
Return $AScX_{t-1}$	.079***
Return $MSCI_t$	.649***
SAD	.000*
DSTC	.003
F-value (p-value)	140.43 (.000)

Output mood model

Table B.5 This table shows the results of the Ordinary Least Squares regression with Newey-West standard errors, which tests the influence of various weather and biorhythm variables on investor mood between 1 January 2006 and 31 December 2015. The values in the table are the betas followed by either *, ** or *** which means significance at the 10%, 5% or 1% level respectively. The dependent variable takes the daily percentage change in closing value of the AEX when the short-run (10-day) moving average is above the long-run (200-day) moving average, which indicates a good mood. Otherwise it takes the value of zero. When a cell is left blank, this means that the variable is not included in the regression analysis.

AEX		
Constant	.002	.000
Monday Dummy	-.000	-.000
January Dummy	-.001	-.000
Return AEX_{t-1}	-.068**	-.069**
Return $MSCI_t$	.999***	.998***
Sunshine	-.000	
Humidity	-.000	.000
Temperature	.000	-.000
Cloud Cover		.000
SAD	-.000	.000
DSTC	-.002	-.002
F-value (p-value)	95.87 (.000)	94.15 (.000)

Table B.6 This table shows the results of the Ordinary Least Squares regression with Newey-West standard errors, which tests the influence of various weather and biorhythm variables on investor mood between 1 January 2006 and 31 December 2015. The values in the table are the betas followed by either *, ** or *** which means significance at the 10%, 5% or 1% level respectively. The dependent variable takes the daily percentage change in closing value of the AScX when the short-run (10-day) moving average is above the long-run (200-day) moving average, which indicates a good mood. Otherwise it takes the value of zero. When a cell is left blank, this means that the variable is not included in the regression analysis.

AScX		
Constant	.001	.002
Monday Dummy	.001	.001
January Dummy	-.000	-.000
Return $AScX_{t-1}$	0.046	.046
Return $MSCI_t$	.548***	.547***
Sunshine	.000	
Humidity	.000	.000
Temperature	-.000**	-.000**
Cloud Cover		-.000
SAD	-.000	-.000
DSTC	.000	.000
F-value (p-value)	54.97 (.000)	55.26 (.000)

Table B.7 This table shows the results of the Ordinary Least Squares regression with Newey-West standard errors, which tests the influence of various weather and biorhythm variables on investor mood between 1 January 2006 and 31 December 2015. The values in the table are the betas followed by either *, ** or *** which means significance at the 10%, 5% or 1% level respectively. The dependent variable takes the daily percentage change in closing value of the AEX when the short-run (10-day) moving average is below the long-run (200-day) moving average, which indicates a bad mood. Otherwise it takes the value of zero. When a cell is left blank, this means that the variable is not included in the regression analysis.

AEX		
Constant	-.004	-.000
Monday Dummy	.002**	.002**
January Dummy	.002*	.002*
Return AEX_{t-1}	-.061**	-.061**
Return $MSCI_t$	1.018***	1.018***
Sunshine	.000***	
Humidity	.000	.000
Temperature	-.000*	-.000
Cloud Cover		-.000**
SAD	-.000	-.000*
DSTC	.002	.002
F-value (p-value)	74.24 (.000)	74.30 (.000)

Table B.8 This table shows the results of the Ordinary Least Squares regression with Newey-West standard errors, which tests the influence of various weather and biorhythm variables on investor mood between 1 January 2006 and 31 December 2015. The values in the table are the betas followed by either *, ** or *** which means significance at the 10%, 5% or 1% level respectively. The dependent variable takes the daily percentage change in closing value of the AScX when the short-run (10-day) moving average is below the long-run (200-day) moving average, which indicates a bad mood. Otherwise it takes the value of zero. When a cell is left blank, this means that the variable is not included in the regression analysis.

AScX		
Constant	-.001	.001
Monday Dummy	.000	.000
January Dummy	.001	.001
Return $AScX_{t-1}$	0.056	.056
Return $MSCI_t$	.672***	.672***
Sunshine	.000	
Humidity	-.000	-.000
Temperature	-.000	-.000
Cloud Cover		-.000
SAD	-.000	-.000
DSTC	.006*	0.006*
F-value (p-value)	51.76 (.000)	52.40 (.000)