The effect of weather on the Amsterdam Exchange Index

An empirical study on the influence of weather on AEX returns in the Netherlands

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Master thesis

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Chapter 1: Introduction

In the last decades, the finance literature dedicated more and more attention to the area of behavioral finance, which discusses irrational investor behavior. The goal of the researchers in this field is to examine investors that do not always behave rationally because of factors influencing their behavior. OED defines irrationality as “the quality of not being guide by, or not being in accordance with, reason; absurdity of thought or action”. Shefrin (2002) connects this definition to finance by stating that human psychology causes investors to fall into the error of perceptual illusions, overconfidence, over-reliance on rules of thumb, and emotions. This study elaborates on irrational investor behavior by investigating the influence of weather on the returns of the AEX index. The reasoning of this study is as follows: (i) prices are mostly rational, though not completely; (ii) because investor decision-making is affected by a person’s mood, which is not rational, one might see price variations; (iii) The condition of the weather is an important factor that influences people’s moods. Subsequently one can thus suggest that the weather indirectly affects decision-making and thus might cause prices to vary.

This thesis assesses if the weather in Amsterdam affects returns of the AEX index, measured over a period of 25 years. To do so, this study examines the returns of Ahold, Heineken, and Unilever, as these AEX listed companies might experience a greater influence of the weather because of the nature of their industry. If one or more of the returns of these three firms shows a significant weather effect, it is necessary to control for this effect when examining AEX returns. Howarth and Hoffmann (1984) find that humidity, temperature and hours of sunshine have the greatest effect on mood. Therefore, the explanatory variables of the model in this research are cloud cover, humidity, precipitation, and temperature. This study includes precipitation because Dowling and Lucey (2002) find a significant effect of rain on Irish stock returns. Additionally, the study at hand computes a model to observe extreme weather circumstances. Here an extreme change in weather between two subsequent days is signaled, as well as an extreme difference in weather in relation to the monthly average. This study uses this extreme weather model to investigate if the weather effect on the AEX index and the selected stocks is stronger when exceptional weather circumstances occur. This research formulated the following hypotheses:

H_0 : the condition of the weather in Amsterdam does not have an effect on investment behavior and therefore the variance in AEX returns does not differ significantly from zero.

H_1 : extreme weather conditions in Amsterdam do not have an effect on investment behavior and therefore the variance in AEX returns does not differ significantly from zero.

According to this theory, if the weather is found to have an influence on AEX returns, returns should increase when temperature increases and when cloud cover, humidity, and precipitation decrease.

The motivation for the research topics in this study is twofold. First, in view of the diverse previous findings regarding the influence of several weather variables on investment decision making and therefore on financial markets in both the Netherlands and other countries, it is interesting to investigate whether a weather effect is present in the Netherlands or not. Specifically, investigating the effect of weather on AEX returns is interesting because the weather in the Netherlands shows some strong variation over the year. Two previous studies investigate the influence of weather on Dutch financial markets so far. Hirshleifer and Shumway (2001) investigate the effect of cloud cover on AEX returns, and do not find a significant effect. Jacobsen and Marquering (2008) investigate the influence of temperature and Seasonal Affective Disorder (SAD) on the value-weighted index of Morgan Stanley Capital in Amsterdam. They find a significant influence of both temperature and SAD on the Morgan Stanley Capital index in Amsterdam. This study distinguishes itself from these two studies in several ways. First, this research uses AEX returns as a dependent variable because this research considers this as the leading stock market index in the Netherlands. Second, this research takes the composition of the AEX index into account, which is important because different types of firms can experience a different weather effect. This study hypothesizes that firms operating in a food and beverage market might be more influenced by the weather. Therefore, this study controls for the weather effect on Ahold, Heineken, and Unilever returns when examining the weather influence on AEX returns. Third, this research considers four different weather variables, being cloud cover, humidity, precipitation, and temperature.

In order to present robust results in this study, three types of weather data are examined; unprocessed data, differences from the previous day, and differences from monthly averages. This study contributes to the literature by using an extreme weather model, which investigates if extreme weather circumstances have a stronger influence on financial markets in the Netherlands than ‘normal’ weather.

The results in this study do not show any influence of the weather in Amsterdam on Dutch stock market prices. First, the weather does not affect the variance in returns of Ahold, Heineken, and Unilever at all. Deducted from these results, there is no need to control for the weather effect on these firms when examining the influence of the weather in Amsterdam on AEX returns. The regressions of AEX returns as a dependent variable do not show that the weather has any influence. In addition, this research does not find any significant results when extreme weather conditions are taken into account.

The remainder of this thesis is structured as follows. Chapter 2 presents a review of the current literature on investment decision-making behavior. In addition, the relationship between weather and mood is discussed as well as the current evidence on weather variables affecting investment behavior. Chapter 3 describes the selected datasets in this research for both weather data and return data. In chapter 4, this study presents the methodology used to investigate whether the weather in Amsterdam influences AEX returns. Chapter 4 also discusses the empirical results of this research. Finally, chapter 5 presents a summary and some concluding remarks.

Chapter 2: Review of the literature

2.1 Introduction

This literature sets the groundwork for the present study about the weather as one of the factors influencing people's moods and with that influencing investment decisions. Therefore, I bring forward important articles in the field of price formation, financial decision-making, the weather effect on people's moods and the influence of mood on financial decision-making.

The traditional finance literature usually assumes that markets are efficient and that investors behave rationally. Traditional economists (Fama for instance) define an efficient market as a market where prices reflect all available information and investors take every decision rationally after thinking through all possible information and outcomes. In this way, all decisions people make are in order to maximize their utility. People are considered to always be capable of arbitrarily complex deductions towards that end. The best-known rational model is von Neumann's and Morgenstern's (1944) expected utility theory, which is the basis for many subsequent traditional finance literature. The theory states that the utility of an investor who is facing uncertainty is calculated by considering utility in each possible outcome and then constructing a weighted average. According to this theory, decision making under risk can be seen as a choice between prospects or gambles; the decision maker must rationally rank his preferences according to the outcomes of various decision options. Expected utility relies on the following three main principles: (i) the overall utility of a prospect is the expected utility of its outcomes, (ii) the domain of the utility function is final states (including the decision maker's asset position) rather than gains or losses, and (iii) decision maker's always behave risk averse.

However, the expected utility model fails to provide a good description of the decision making process because people usually do not have all information necessary to make a decision. In addition, they lack the ability to combine and weigh the information rationally. Kahneman and Tversky (1979) show that the three main principles of the expected utility hypothesis are often violated. They demonstrate that decision makers take the final state of their assets into account. More importantly, investors display risk aversion when they are in a winning state, but display risk seeking behavior when in a losing state. They conclude that decision makers certainly do not always behave rationally, and that many factors, i.e. personal risk attitude or reference point, might be of influence in the decision making process. In addition, a decision maker's mood and current emotions might be of great influence on behavior in the decision making process. Kahneman and Tversky show that, in the area of finance, many factors might cause markets to deviate from working efficiently. This is an important topic in the behavioral finance literature. Behavioral finance assumes that "psychology is the basis for human desires, goals and motivations, and it is also the basis for a wide variety of human errors that stem from perceptual illusions, overconfidence, over-reliance on rules of thumb, and emotions" (Shefrin, 2002).

This literature review discusses how both traditional and behavioral finance consider people's decision-making process and how this influences price formation. Specifically, I discuss the distinction finance makes between rational and irrational behavior of people. The finance literature concludes that people do not always make rational decisions and an important reason for this is that a decision maker's mood and emotions at the time of the decision influence the decision making process. Happy people are more optimistic in making choices than sad people (Bower and Cohen, 1982 and Blaney, 1986). In addition, happy people are less critical in processing information, where sad people on the other hand tend to overanalyze details in the decision process (Schwarz, 1990). In turn, moods are for a severe part proved to be influenced by the condition of the weather. Positive moods are positively correlated with hours of sunshine and temperature, while they are negatively correlated with humidity and precipitation for instance (Howarth and Hoffmann, 1984).

As weather influences people's moods and people's moods influence people's decision-making process, it can be argued that investment decisions are affected by the weather condition at the time of the decision. As a result, people's investment decisions affect stock prices. In this line of reasoning, the weather is thus influencing these prices. If this is the case, investors do not behave rationally and markets are not efficient. In the final section of this chapter, I examine several empirical studies that discuss the influence of weather on the decision making process of investors. Even though most studies find that weather factors affect financial market investors, it should be noted that none of the studies finds empirical evidence that can explain investor's behavior totally, and that weather can thus only explain a small part of the puzzle.

2.2 Finance – Efficiency and price formation

Traditional finance literature normally assumes that markets are efficient and that investors behave rationally. As mentioned above, traditional economists (Fama for instance) define an efficient market as a market where prices reflect all available information and investors take every decision after thinking through all possible information and outcomes. In this way, all decisions people make are in order to maximize their utility and all people are always perfectly capable to make the best decision. Behavioral finance assumes that "psychology is the basis for human desires, goals and motivations, and it is also the basis for a wide variety of human errors that stem from perceptual illusions, overconfidence, over-reliance on rules of thumb, and emotions" (Shefrin, 2002).

Before 1970 investment theory centered on the assumptions of rational investors and efficient behavior of financial markets. In 1970, Fama, a traditional economist, unified these theories and summarized them as the efficient-market hypothesis (EMH). The EMH assumes that financial markets are informationally efficient, which simply means that prices on traded assets already reflect all available information. Therefore the EMH requires that agents aim to maximize utility, that agents have rational expectations, that on average the investor population is rational (even if no single investor is), and that when new information appears, agents update their expectations immediately. Rational expectations can be defined as being 'the best guess of the future' that uses all available information. Fama distinguishes three versions of the EMH based on the level of available information. The weak form EMH stipulates that current asset prices already reflect past price and volume information of the asset. The semi strong EMH states that all publicly available information is similarly incorporated into the price of the asset. This way, both weak form and semi strong EMH imply that no one should be able to outperform the market using something that 'everybody else knows'. Finally, strong EMH stipulates that private information or inside information too, is incorporated into the price of the asset. Thus, all information, whether public or private, is fully reflected into the price of the asset. For all three versions, EMH makes no prediction about human behavior and assumes that people do not make systematic errors when making decisions. With the requirements mentioned above, Fama notices that when investors are faced with new information, some may overreact and others will underreact. Elaborating on his 1970 study, in 1998 Fama finds that overreaction of stock prices to information is about as common as underreaction. In addition, he finds that long-term return anomalies, studied by many authors in order to reject the EMH (i.e. DeBondt and Thaler, 1985; and Loughran and Ritter, 1995), are fragile and mostly chance results, which is indeed consistent with EMH.

Behavioral finance analysts do agree with Fama that investors might behave irrationally, but they strongly reject the assumption that the investor population is rational on average. Shiller (2003), a disciple of behavioral finance, reviewed the EMH as well as other efficient market models and theories, and accurately described the history of behavioral finance. He concludes that the development of behavioral finance has led to "a profound deepening of our knowledge of financial markets". Although he is aware of the fact that in normal market conditions market efficiency is not false to assume, he warns that in extreme market situations, the efficient market hypothesis could lead to "drastically incorrect interpretations". A stock market bubble is a good example of an extreme market situation that is often not interpreted as such and that is often still considered as efficient. Shiller ends his article by stating that it is a challenge for economists to include reality into their models. For him, reality indicates that apparently efficient markets are not always efficient.

Black (1986) elaborates on the EMH and the rational expectations theory in his article about noise. He defines noise as follows: "Noise is what makes our observations imperfect. It keeps us from knowing the expected return on a stock or portfolio". Black tries to answer the following question in his article: if investors do know noise is present, why do people trade on noise? His answer on this question is "One reason it that they like to do it. Another is that there is so much noise around that they don't know they are trading on noise. They think they are trading on information". He claims that both these reasons do not correspond to a world where people only make decisions in order to maximize their utility, and where people always make the best use of available information. The most important lesson here is that people do not always make rational decisions and that markets thus do not work always efficiently.

2.3 Psychology - theory of decision making

People do not always behave rationally and markets do not always work efficiently. An important cause for people's irrational decision-making behavior is the influence of people's emotions on this process. In the area of psychology, a broad literature discusses the effects of people's moods and emotions on human behavior. Wright and Bower (1992) argue that, in order to make a decision different choices and their probabilities of happening are examined by retrieving information from long-term memory. In this context probability is a way to represent an individual's degree of belief in a statement. The manner and amount of memory retrieval is affected by a person's mood, which leads to a person's mood having an effect on decision making as well. Within the article, Wright and Bower recall three findings on affect and cognition from Bower and Cohen (1982) and Blaney (1986): (i) feelings act as a selective attentional filter for incoming stimuli, focusing attention on aspects of the situation that are consistent with the mood. Feelings therefore partially determine how a stimulus is encoded in memory; (ii) feelings affect what information is subsequently retrieved from memory, a mood-context retrieval effect (iii) apart from any memory retrieval effects, feelings influence the availability of different constructs and strategies used in arriving at social perceptions, personality assessments, risky decisions (such as investments), and other judgments, i.e. the processing of information to yield a conclusion, and the quality of such conclusions. Their results indicate that happy people are more optimistic in making judgments and choices than sad people, i.e. they are assigning positive events as highly probable and negative events as less probable. For investing, this implies that happy people tend to invest sooner because they assign positive events (i.e. an increase in stock price after buying the stock which leads to a gain) as more probable than negative events (i.e. a decrease in stock price after buying the stock which leads to a loss). In addition, Schwarz (1990) finds that people in good moods are more likely to show heuristic behavior and are less critical in processing information. People in bad moods on the other hand tend to overanalyze details in the decision process. This overanalyzing might cause ill-tempered people to mainly consider the negative sides of investing. On the other side, good-tempered people that show heuristic behavior (behavior based on rules of thumb, educated guesses and intuitive judgments) might only consider the positive sides of investing. However, both good- and ill-tempered moods probably lead to irrational decisions.

Loewenstein et. al. (2001) developed a “risk-as-feelings” model which acts as a descriptive model of decision making under conditions of risk and uncertainty. They specifically try to explain how decision making under the influence of feelings is different from rational decision-making. Due to either lack of information or excessive information or several cognitive constraints, people are not always able to make rational decisions when faced with complex problems, like investing. In this case, people tend to make satisfactional, rather than optimal decisions and, surprisingly, people tend to turn to their emotions to help them make these satisfactional emotions. These decisions naturally cannot be called rational.

In addition, Johnson and Tversky (1983) discuss how people perceive and evaluate risk and find that mood has a severe impact on judgments of risk. They argue that decisions and judgments are strongly influenced by feelings and emotions and thus not only by rational thinking.

2.4 Weather and mood

People's moods and emotions influence human behavior and decision-making. This in turn might cause irrational stock price effects, like AEX index returns that significantly differ from zero. The weather, specifically hours of sunshine, humidity and temperature, can be of significant influence on moods and emotions (Howarth and Hoffmann, 1984; Cunningham, 1979; and Persinger, 1975). In this line of reasoning, the weather might thus indirectly affect stock prices. Howarth and Hoffmann relate ten mood variables to eight weather variables in a multidimensional study. The mood variables are as follows: concentration, cooperation, anxiety, potency, aggression, depression, sleepiness, skepticism, control, and optimism. The weather variables include: hours of sunshine, precipitation, temperature, wind direction, wind velocity, humidity, change in barometric pressure and absolute barometric pressure. They find that humidity, temperature and hours of sunshine have the greatest effect on mood. Good moods are positively correlated with hours of sunshine, while they are negatively correlated with humidity. Temperature normally has a positive influence on people's moods, unless the temperature is too high, i.e. when it becomes unpleasantly hot. Cunningham conduct two field studies on the relationship of weather variables to 'helping behavior'. Like Howarth and Hoffmann, he finds that the amount of sunshine is a very strong predator of willingness to help someone, as well as temperature, humidity, wind velocity and lunar phases on a lower level.

2.5 Weather and investment decision making

As is explained above, people's moods influence their decision making process; and the state of the weather influences people's moods. The next step in this line of reasoning is to describe how the weather affects people's investment decision making. Several authors have examined this weather influence on the behavior of market traders and thus on financial markets. The first to write about the influence of weather on financial markets is Roll (1984). He examines the interaction between prices of frozen concentrated orange juice futures contracts and weather as a truly exogenous determinant of value. Roll's results indicate that orange juice futures prices are slightly, but significantly influenced by cold temperatures but no influence of rainfall on prices is detected. He finds no other demand or supply factors to be of significant influence to explain daily price movements in orange juice futures. Even though this study finds that weather is the most obvious and significant driver of orange juice prices, weather can only explain a small fraction of the variability in futures prices so there still is a large amount of inexplicable price volatility. On first sight, a review of Roll's paper might seem somewhat strange in this research because he investigated the influence of weather on futures prices of one single product. However, since Roll was the first author to write about the influence of weather on any financial market, he has inspired many other authors to investigate the weather effect on other types of financial markets, like the Amsterdam Exchange Index in this study.

In terms of evidence about market traders' behavior caused by weather, Saunders (1993) at first shows that the amount of cloud cover in New York City is positively correlated with the major stock indexes in New York and that this weather effect casts doubt on the rationality of securities markets. Six types of daily end-of-day meteorological data, from January 1st 1927 to December 31st 1989, were provided by the National Climatic Data Center; temperature, relative humidity, precipitation, wind, sunshine, and cloud cover. However, this research only uses daily cloud cover percentages as weather variable. For stock price indexes this research uses three different variables: daily percentage changes in the Dow Jones Industrial Average (DJIA) from January 1st 1927 to December 1st 1989; and equal- and value-weighted daily percentage changes in the NYSE/AMEX index (returns excluding dividends) from July 6th 1962 to December 31st 1989. First, data on percentage cloud cover are paired with daily stock price index prices and mean percentage daily change and frequency of positive daily changes are calculated. The results indicate that the lower the percentage of cloud cover, the higher is the mean return of stock prices, which indicates that the amount of cloud cover indeed has a significant effect on market traders' behavior. Within this part of his study, Saunders compares 0-20 percent cloud cover returns with 100 percent cloud cover returns. In a second series of regressions day and month dummies are included to control for season and market anomalies like the January, weekend and small firms effect. However, results still indicate that New York City cloud cover is significantly correlated with index returns. Finally, Saunders finds that the relationship between changes in stock prices and weather decreases for the period from January 1st 1983 through December 31st 1989, though remains positive.

Trombley (1997) elaborates on Saunders results by using the same data differently. Contrarily, he finds that the effect of cloud coverage on NYC stock indexes is not as strong as Saunders reported and only appears in some months of the year. Within the article, Trombley finds that the returns on 0 percent cloud cover days do not significantly differ from 100 percent cloud cover days. However, the study finds a significant difference in returns on 10 percent and 100 percent cloud covered days. Trombley argues that Saunders choice only to compare 0-20 percent cloud cover day returns and 100 percent cloud cover returns is "the only comparison during this period that would produce a statistically significant test statistic and does not consider that the returns on the 0 percent days are inconsistent with the existence of a weather effect". When controlling for season and market anomalies by using multiple regressions, also no significant difference between 0 and 100 percent cloud cover day returns is identified. Likewise, the difference in returns on 10 and 100 percent cloud cover days is much less obvious when season and market anomalies are taken into account and not even existent in five out of twelve months. Finally, Trombley's results indicate that in the period before 1962, there was no weather effect at all. Unfortunately, the article provides no reasons for why the weather effect is limited to the recent past and why the effect exists in some months and not in others.

Hirshleifer and Shumway (2001) also elaborated on Saunders' study and extended it to 26 major stock markets in the world. In order to test the hypothesis that sunshine affects returns on stock markets, they examine the relation between daily cloudiness and daily returns on the nation's stock index for each city individually. Weather data, retrieved from the International Surface Weather Observations dataset, contain detailed weather data at 3,000 locations worldwide from 1982 to 1997. First, they calculate and deseasonalize average daily cloud cover from 6 AM to 4 PM in order to be certain that results are driven by cloudiness and not by other seasonal effects. They also include daily measures of deseasonalized raininess and snowiness in most regressions in order to check whether adverse weather effects drive results. Stock return data for all cities that have data available from at least 1988 to 1997 are included in the analysis. To mitigate well-known seasonal stock effects, the deviation between the day's cloudiness and the expected degree of cloudiness for that particular day is examined and reveals a genuine relation between stock returns and cloudiness in some cities. However, for Amsterdam stock market returns, Hirshleifer and Shumway do not find any effect of cloudiness. When providing parametric joint (cross-city) tests using the entire dataset, they again find that sunshine is highly correlated with daily stock returns all over the world. For both city-by-city results and cross-city results there is no evidence that other weather conditions as rain and snow are related to stock returns. Hirschleifer and Shumway conclude that even though the amount of sunshine is of significant influence on stock market volatility, it is just one of many elements affecting mood and thus equally one of many elements affecting investors' behavior.

Dowling and Lucey (2002) on the other hand do find that rain, as well as other variables, has a small, but significant effect on the stock market in Ireland when examining the influence of several mood variables on the stock market. They collect daily stock returns from both the Irish Stock Exchange Official Price Index (which is a value-weighted index of equities listed on the Dublin Stock Index) and the FTSE All-world Index from October 14th 1988 to December 29th 2000. Then they calculate the local component of Irish stock returns by subtracting the daily return on the world index from the daily return on the Irish index. The reason for finding a local component of Irish stock returns is that Dowling and Lucey believe that mood variables are most likely to affect that component of the returns and thereby they hope to find better results by concentrating on the local component only. Within their research, they include several mood variables; cloud cover, precipitation, humidity, geomagnetic storms as weather proxies; Seasonal Affective Disorder (SAD, a condition that affects many people during seasons of relatively fewer hours of daylight) and Daylight Savings Time Changes (DSTC) as biorhythm proxies; and lunar cycles and Friday the 13th as belief proxies. Daily weather observations came from Met Eireann, geomagnetic storm data from the National Geophysical Data Centre and finally, lunar cycle data from www.lunaroutreach.org. This research uses mainly OLS regressions with heteroskedasticity-robust White standard errors, though however in some data, non-normality is found and then LAD and TLS specifications are included. Contrarily to others, Dowling and Lucey do not find a significant relationship between cloud cover and stock market returns, although they find relationships between Irish equity returns and rain, Daylight Savings Time Changes, Seasonal Affective Disorder and lunar cycles. In addition, they find preliminary support for the hypothesis that people in positive moods are more susceptible in their decision-making to the influence of irrelevant factors.

Goetzmann and Zhu (2002) present a different approach to measure the weather effect by using a dataset of individual investors living in five large US metropolitan areas. Their data contains information on anonymous investor characteristics, trade date, securities identification, trade quantity, and price, and it runs from January 1991 to November 1996.

Firstly, they transform Hourly Total Sky Cover (SKC) data from the National Oceanic and Atmospheric Administration into daily measures by taking the average of each day's trading hours. To control for seasonal patterns and to capture the unexpected component of a day's weather change, they also calculate a daily seasonally adjusted SKC. This research defines the net buy in shares as the total number of shares of stocks bought minus the total number of shares of stocks sold by the sample individuals on a particular day. On the other hand, they calculate the buy-sell imbalance in dollar value by subtracting the dollar values of selling trades from the dollar values of the buying trades, and then dividing the outcome by the daily average of total value of stocks traded by sample investors. First, they regress the NYSE index daily return on New York City's sky cover to confirm previous findings that the stock return is indeed higher on sunny days and that a weather effect is significantly present. Looking at the empirical results though, Goetzmann and Zhu do not find significant differences in trading volume by individual investors on sunny or cloudy days for all five cities. The next thing they examine is the expectation that it is the marginal investors that are likely to be influenced by the weather, but here also no evidence is found. Finally, they hypothesize that market makers at the NYSE might be influenced by New York weather, which they examine by looking at the daily relation between the average bid-ask spread change and NYC weather. Here they find a small, but significant relationship, which suggests that changes in risk-aversion of the NYSE specialist might be induced by weather.

In Spain, no effect of weather on stock returns in found (Pardo and Valor, 2003). This article distinguishes itself from the others by taking into account the fact that stocks could be floor or screen traded. They use daily closing values of the Madrid Stock Exchange Index from January 1981 through May 2000, whereas the system changed from floor trading to screen trading in April 1989. Daily weather variables, sunshine hours and relative humidity, are from the Instituto Nacional de Metereologia. First, they split the dataset in two sub-periods, where the weather effect is expected to be stronger in the first, floor-trading, period. Then they separate the daily returns into sunshine hours and relative humidity quintiles, so that the fifth quintile immediately shows what the weather effect on stock prices is. Empirical evidence of this study shows that, for both sub-periods, there is no influence of sunshine or humidity on stock prices. Based on these results, Pardo and Valor conclude that the Spanish stock market behaves rationally. With that, they fail to take into account many other factors, besides the weather, that can lead to irrational markets. Examples of other factors that cause irrationality are momentum effects, overpriced stocks, bubbles and crashes.

Kamstra, Kramer, and Levi, (2003) and Cao and Wei (2005) both claim that a seasonal anomaly in stock returns is caused by mood changes of investors due to lack of daylight and temperature variations, respectively. The former authors investigate the influence of daylight (SAD) on four US indices and eight indices in other countries, chosen to represent large-capitalization, broad-based economies at different latitudes in both hemispheres. Since all indices differ in data availability sample sizes range from 3,000 to 19,000 daily index return observations. Daily SAD data are simply calculated by subtracting the number of hours of day from 24 for each country. For each country, they run single regressions, while controlling for the Monday effect, a tax-selling effect and the fall effect (which can be seen as a bad period after a longer good period). The evidence found in this article supports the existence of an effect of Seasonal Affective Disorder on stock market returns around the world. As could be expected, this effect is greater the higher the latitude. In addition, the impact of SAD in the Southern Hemisphere is out of phase by six months relative to the North, which is also expected.

Cao and Wei hypothesize that “lower temperature is associated with higher stock market returns due to aggressive risk taking, and higher temperature can lead to either higher or lower stock returns since both aggression (associated with risk-taking) and apathy (associated with risk-averting) are possible behavioral consequences and the net impact on investors’ risk taking depends on the trade-off between the two”. In the article, they analyze nine stock indices in eight countries. Daily temperature data are from the Earth Satellite Corporation, where the average of minimum and maximum-recorded temperature is taken as temperature variable. For each index, the sample period is different. The earliest starting date is July 3rd 1962, while the latest ending date is July 9th 2001. First, they group returns according to temperature ordering and analyzed the statistical difference between return-groups. Then, similar to Kamstra et al. (2003), for each country they run single regressions, while they controll for the Monday effect and a tax-selling effect. Results of these tests indicate that indeed stock returns are negatively correlated with temperature, where they find stronger relationships in the winter. This implies that when temperature is high, apathy dominates aggression, resulting in lower returns.

A very recent study by Jacobsen and Marquering (2008) elaborates on the findings of both Kamstra et al. and Cao and Wei. They investigate the monthly returns on the value-weighted indices of Morgan Stanly International Capital of 48 countries from January 1970 to May 2004 or shorter. Average monthly temperature data are from the Global Historical

Climatology Network. The simple OLS regression results suggest that there is a strong and robust seasonal pattern in stock returns. For the Netherlands, Jacobsen and Marquering find that both temperature and SAD have a significant influence on returns on the value-weighted index of Morgan Stanley Capital in Amsterdam. However, for all countries counts that when one of the two variables, either SAD or temperature, is included as dummy variable in the regression, the other one becomes redundant. This result suggests that these correlations might be spurious. Therefore, one cannot conclude that weather influences stock returns through mood changes of investors. In fact, many things are correlated with the seasons and it is difficult to distinguish among them when trying to explain seasonal patterns in stock markets. Furthermore, Jacobsen and Marquering find that stock markets in countries closer to the equator react stronger on temperature changes than stock markets in countries further away from the equator do.

2.6 Summary

The line of reasoning in this research is summarized as follows: (i) prices are mostly rational, but not completely; (ii) because investor decision-making is affected by a person’s mood, which is not rational, one might see price variations; (iii) The condition of the weather is an important factor that influences people’s moods. Subsequently one can thus suggest that the weather indirectly affects decision-making and thus might cause prices to vary. In the financial empirical work field, several authors do find a significant relationship between the weather and financial markets and others do not. In general, empirical studies find that financial markets are positively influenced by good weather and negatively by bad weather. However, results differ per country and not for all countries significant evidence of the weather effect is found. Within the next chapters, I will examine if the condition of the weather in Amsterdam influences the Dutch stock market index and selected Dutch stocks.

Chapter 3: Data

3.1 Introduction

As explained in the literature review chapter, Howarth and Hoffmann (1984) conclude that the weather variables humidity, temperature, and the amount of cloud cover have the greatest effect on people's moods. People's moods in turn can have an effect on people's investment behavior and thus on AEX returns. Therefore, this study uses these three weather factors to investigate if the weather has an effect on AEX returns. In addition, the amount of rainfall is included in this investigation because Dowling and Lucey (2002) find a significant effect of this variable on the Irish Stock Market.

In order to perform an accurate empirical study of the data, it is important to understand the collection and organization process of the data. This chapter first describes three AEX-listed companies, being Ahold, Heineken and Unilever. As these firms operate in the food and drinks market, there is a possibility that the condition of the weather has a greater impact on the returns of these firms. If this is the case in this research, it is necessary to control for the weather effect on these firms when I examine the weather effect on the AEX index. Next, this section describes the history and composition of the AEX index as well as the computation of daily returns. Furthermore, this chapter presents where the weather data for the Amsterdam weather station was collected and how the Koninklijk Nederlands Meteorologisch Instituut (Royal Dutch Meteorological Institute, KNMI) retrieves these data. Also is described how to deal with seasonality in the data and how 'extreme change of weather days' are computed.

3.2 AEX returns data

3.2.1 Ahold, Heineken and Unilever

Before investigating whether the weather in Amsterdam is affecting the AEX index, this research investigates the weather effect on three particular AEX listed companies, being Ahold, Heineken and Unilever. Companies in some markets might be more affected by the weather than firms in other markets. Ahold is a food retailer and wholesaler, Heineken is a brewer, and Unilever is a consumer products company. From this, this research hypothesizes that firms operating in a market with food and drinks are more affected by the state of the weather. If this is the case, this study should control for the influence on these firms when investigating the weather effect on the AEX index as a whole.

All three mentioned companies are part of the AEX index from the first moment, from January 3rd 1983. Price data for these firms are retrieved from DataStream for the period January 3rd 1983 to May 30th 2008. This study calculated logarithmic returns for Ahold, Heineken and Unilever with the following formula:

$$(1) \qquad R_t = \log(P_t / P_{t-1})$$

where P_t and P_{t-1} are closing prices of either Ahold, Heineken or Unilever on days t and t-1, respectively. Saturdays and Sundays are not reported, and other non-trading days, like public holidays, are removed from the time series.

Table 4 provides descriptive statistics on Ahold, Heineken, and Unilever. Over time, Ahold holds the highest mean return with 0.031% as well as the highest standard deviation of 1.05%. The lowest log return is -43.4%, measured on February 24th 2003; the day one of the greatest accounting scandals was discovered. The maximum observed daily log return for Ahold is high as well with 13.1%. Taken all together, the Ahold accounting scandal caused large drops in stocks and later also large stock increases. Heineken's average daily return is 0.026% with a standard deviation of 0.68%. The lowest measured return of the Heineken stock over time is -6.0%, where the highest is 4.9%. Unilever holds the lowest mean return with 0.016% as well as the lowest standard deviation of 0.55%. The lowest measured return for Unilever is -5.5%, the highest positive return is 4.9%. To conclude, of these three firms, Unilever's stock is the least volatile and risky over time.

In terms of the distribution of Ahold, Heineken and Unilever, negatively skewed distributions are found (the mass of the distribution is skewed on the right). This suggests that daily mean temperature is non-normally distributed, which is also confirmed by the Kolmogorov-Smirnov test for normality. This test decides whether a data sample has a specified distribution, a normal one in this case. The Kolmogorov-Smirnov test statistic is defined as:

$$(2) \qquad D = \max_{1 \le i \le N} \left(F(Y_i) - \frac{i-1}{N}, \frac{i}{N} - F(Y_i)\right)$$

where F is the theoretical cumulative distribution of the distribution being tested. For normality testing, Lilliefors made minor improvements to this test. However, in order to test the time series data in this study for normality, not solely the outcomes of the Kolmogorov-Smirnov test are examined, but also the plotted histograms of time series in figures 1 to 16 are viewed whether these display a normal bell-shaped curve. Figures 14 to 16 plot the histograms for Ahold, Heineken and Unilever returns, and indeed these figures show that the data do fit the curves quite well and therefore one can conclude that these time series are normally distributed.

3.2.2 History and composition of AEX index

The Amsterdam Exchange Index (AEX) is a stock market index composed of companies that trade on Euronext Amsterdam (formerly Amsterdam Stock Exchange). The index started on January 3rd 1983 as European Options Exchange and is composed of a maximum of 25 of the most actively traded securities on the exchange. At that time, the AEX was the first stock exchange in Europe and listed 13 companies. The name Amsterdam Exchange Index is used from January 1st 1994. Currently, the AEX is one of the main national indices of the stock exchange group Euronext. At the start in 1983, the AEX index had a base level of 45.38 points (100 points in Dutch guilders). At the end date of the dataset used in this study, May 30th 2008, the closing value of the index was 485.52, where the all time peak of the index is 703.18, reached on September 5th 2000.

Before 2008, the AEX index composition was reviewed once a year on the first trading day in March, but from this year on the AEX index composition will be reviewed twice a year in both March and September. The review is based on the closing prices on the final trading days of January and June, changes made to the composition are effected on the following trading day. At each review date, the 25 firms with the highest share turnover over the previous period will be admitted to the index. Furthermore, when one firm has more than one class of shares traded on the exchange, only the most actively traded one is allowed to be included into the index. At the review date, also the weightings for each firm are calculated with respect to the closing prices of the firms at the first trading day in March. This change in AEX composition does not have a severe implication for the research at hand since the used dataset in this study ends at May 30th 2008, and the first extra review takes place later on in September 2008.

At this moment, not 25 but only 21 companies are included in the index. This is possible because if a firm is removed from the index due to delisting, acquisition, or any other reason, it is not allowed to make any replacements until the next review date. Table 8 presents an overview of the currently included companies in the AEX index. The value of the AEX index consists of a basket of shares based on the firms' weights and index value at the time of the readjustment. In order to mitigate the influence of the biggest firms in the index, a cap is set at

15%. The AEX value is calculated every 15 seconds by first multiplying the price of each of the stocks by the number of shares of that stock in the basket and then summing the outcomes and dividing by 100.

3.2.3 Computation of daily AEX returns

Having obtained the AEX price data for January 3rd 1983 until May 30th 2008 from DataStream, I calculated daily AEX returns using the following formula:

(3) $$R_t = \log(P_t / P_{t-1})$$

where P_t and P_{t-1} are closing prices of the AEX index on days t and t-1, respectively. Within the AEX return time series, Saturdays and Sundays are not reported. Other non-trading days, public holidays for instance, are removed from the time series. This study uses logarithmic returns rather than arrhythmic returns, because logarithmic returns have the distinguishing mark of being symmetric, which in this context means that positive and negative percent returns are equal.

Table 4 presents descriptive statistics for the AEX log returns. The average daily logarithmic return is slightly positive with 0.021%. This is a normal number considering the Efficient Market Hypothesis, which expects returns to be zero. The corresponding standard deviation is larger with 0.729%, which is not very surprising considering the range of 12%. The minimum log return observed within the period 1983-2008 is -5.7%, while the maximum observed return is +6.2%. Just like the weather variables, the AEX log return might be non-normal distributed, considering the negative skewness and the outcome of the Kolmogorov-Smirnov test. The histogram in figure 13, however, shows that this time series fits the curve well enough to conclude that this variable is normally distributed.

3.3 Weather data

3.3.1 KNMI daily weather data collection

All weather data used in this study are retrieved from the Koninklijk Nederlands Meteorologisch Instituut (Royal Dutch Meteorological Institute, hereafter called KNMI). The KNMI, established in 1854, and with its headquarters in De Bilt, has as primary tasks to forecast weather in the Netherlands, to monitor climate changes and to monitor seismic activity. In addition, KNMI is the national research and information centre for climate,

climate change and seismology. Today, KNMI measures daily weather data at ten weather stations dispersed over the Netherlands. A map with these weather stations is presented in the appendix. For De Bilt daily weather data are available from 1901 on; for Den Helder, Groningen, Vlissingen and Maastricht from 1906 on; for Amsterdam, Twente, Eindhoven and Leeuwarden from 1951 on and finally for Rotterdam from 1956 on. On a daily basis, the KNMI retrieves measures wind direction wind speed per day and per hour and highest squall per day; mean, minimum and maximum temperature; sunshine duration and the percentage of the highest possible sunshine duration on that day; precipitation amount and duration; mean surface air pressure, minimum visibility, cloud cover in octants and mean relative atmospheric humidity in percents.

Temperature is reproduced in degrees Celsius and is measured on a height of 1.5 meter. Daily mean temperature is the average of 24 hourly observations within the full day. Maximum and minimum temperature are respectively the highest, and the lowest observations on a particular full day.

KNMI calculates sunshine duration from ten-minute radiation observations using an algorithm developed for the KNMI. The relative sunshine duration, on the other hand, is the percentage of the occurred time of sunshine in relation to the maximum possible sunshine duration on that particular day. Cloud cover is determined every hour and reported in octants which run from ‘cloudless’ to ‘sky invisible’. The reported daily cloud cover data is the average of 24 hourly observations within the full day. Next, minimum visibility is witnessed every hour by recognizing definite objects surrounding the survey station. The observing person should be aware of the effective distance of the objects and can therefore measure the visibility.

Mean surface air pressure is reproduced in hector Pascals (one hPa equals one mbar) and is the average of 24 hourly observations within the full day. Hourly observations are based on a permanent measurement in the course of one minute. KNMI presents relative atmospheric humidity in percentages, where a value 100% means that the air is saturated with water vapor, and low values indicate a dry atmosphere.

Rain, drizzling rain, super cooled rain, snow, hailstone, glazed frost, and icicles all fall under precipitation. KNMI expresses the amount of precipitation in millimeters of rainwater. Ten millimeters on one square meter equal ten liters of rainwater on a square meter. Precipitation duration is the cumulative time on a full day where precipitation is measured.

Finally, wind is measured ten meters above the surface and described in 0.1 meters per second. The average wind speed is the mean of 24 hourly mean observations within a full day. KNMI expresses the highest of these hourly mean observations as highest wind speed per hour, while the highest measured highlight in wind speed is expressed as highest squall.

3.3.2 Choice of Amsterdam weather station

As described in the previous section, the KNMI observes the weather in the Netherlands from ten different weather stations. For the purpose of this thesis, data from the Amsterdam weather station are used. Daily weather data for Amsterdam are available from January 1st 1951. However, this study uses solely data from January 3rd 1983 to May 31st 2008 as AEX data are only available for this time period.

There are several reasons to choose Amsterdam as most suitable weather station when one wants to examine the effects of the weather on the AEX index. First, as the name already mentions, the AEX index is the most important indicator of Euronext Amsterdam, formerly called Amsterdam Stock Exchange and is thus located in Amsterdam. Besides, Amsterdam is the capital and the biggest, most important city in the Netherlands. Furthermore, Amsterdam is in the centre of the 'Randstad', which is the agglomeration of major cities in the Netherlands. Looking at population, the provinces surrounding Amsterdam, being Noord-Holland, Zuid-Holland, Utrecht and Flevoland, inhabit about half of the total population of the Netherlands, as is presented in the appendix. This means that the condition of the weather in Amsterdam works as an indicator of the weather condition acknowledged by about 7.7 million people on a certain moment. Finally, when examining high-income municipalities, the majority is situated nearby Amsterdam (based on figures retrieved from CBS, Centraal Bureau voor de Statistiek, the Dutch national institute for statistics). This is important for the AEX index since individuals who tend to invest in listed companies are mostly people with higher than average incomes. To conclude, besides to being the business centre of the Netherlands, Amsterdam and its surroundings house approximately half of the population of the Netherlands. In addition, the majority of high-income municipalities are located nearby Amsterdam. All these factors together make the Amsterdam weather station the best choice for the purpose of this study.

3.3.3 Organization of data

In order to find out whether the weather in Amsterdam effects AEX index returns, this study uses three different types of weather data, being unprocessed data (UP), deseasonalized calculated differences in relation to the previous' days weather (FD), and deseasonalized calculated differences in relation to the average monthly weather (SA). This research reproduces all four weather variables in this study - cloud cover, humidity, precipitation, and temperature – in time series of all three types of weather data.

Unprocessed data (UP data)

Unprocessed data (UP) are simply the observed and documented data retrieved from the KNMI. As already mentioned, these data range from January 1st 1983 to May 31st 2008. As Saturday and Sunday are not trading days in Amsterdam, these days are removed from the time series. The same applies to other non-trading days, like public holidays. In total, there are 6,545 weather observation days within this period.

Temperature

Table 1 presents descriptive statistics for the unprocessed weather data. For daily mean temperature, the average over all years is 10.25 degrees Celsius, with a standard deviation of 6.07 degrees Celsius, which is a high number. However, as these data are unprocessed, this result is not unexpected since there is a strong seasonality effect present in these data. The lowest observed daily mean temperature is -12.3 degrees Celsius and is observed on January 14th 1987. The highest observed daily mean temperature, on the other hand, is 26.7 degrees Celsius and is observed on July 19th 2006. The range between these minimum and maximum observations is 39.0 degrees Celsius. In terms of the distribution of daily mean temperature, a small, but negatively skewed distribution is found (the mass of the distribution is skewed on the right). This suggests that daily mean temperature is not normally distributed, which is also confirmed by the Kolmogorov-Smirnov test for normality. However, figure 1 plots the histogram for daily mean temperature and this plot shows that the data do fit the normally curve quite well and therefore one can conclude that this time series is normally distributed.

Precipitation

The average observed daily precipitation amount over all years is 2.33 millimeters. For this variable, also a high standard deviation is measured, that is 4.70 millimeters. For the same reason as described above, the presence of a seasonality effect in the data, this measure is not surprising. The minimum amount of precipitation is 0 millimeter (even though days with precipitation less than 0.05 mm are marked as -1), where the maximum amount is 56.7 millimeters, observed on July 4th 2005. As a consequence, the range between these minimum and maximum observations is 56.7 millimeters of precipitation. In terms of distribution of the daily amount of precipitation, a positively skewed distribution is present (which means that the mass of the distribution is skewed on the left). Looking at the histogram in figure 2, one cannot conclude that this precipitation time series is normally distributed.

Cloud cover

The average observed cloud cover over all years is 5.2 octants, which is half to heavy cloudy. Again, the standard deviation, which is 2.1 octants, is quite high but not unexpected. For cloud cover, all different octants do occur in the 1983-2008 period. However, table 5 shows that cloud cover octants 6 and 7 are observed most frequently over time. Cloud cover octant 0, on the other hand, is only observed on 212 days, which is 3.2%. From this, one can conclude that the Netherlands is covered in clouds most of the sample period. Looking at the cumulative percentages in table 5, it is possible that this variable is not normally distributed, which is confirmed with the negative skewness number and the outcome of the Kolmogorov-Smirnov test. However, the histogram in figure 3 follows the normality curve well enough to consider this variable normally distributed.

Humidity

The average observed daily mean relative atmospheric humidity in percents is 83.1%, with, contrary to the other unprocessed weather variables, a small standard deviation of 9.5%. The lowest percentage of humidity measured between 1983 and 2008 is 38%, where the highest measured percentage of humidity is 100% in the same period. In addition, humidity has shown a small, negatively skewed distribution, but the histogram in figure 4 shows that this variable is normally distributed.

Seasonality - difference in relation to the previous day (FD data)

The next type of examined weather data is the observed first difference in relation to the previous day (FD) and is thus a deseasonalized type of data. Again, the four weather variables cloud cover, humidity, precipitation, and temperature are calculated using the following formula:

(4) $$\Delta Y_t = Y_t - Y_{t-1}$$

Here also Saturdays, Sundays and public holidays are removed because they are not trading days. However, before removing them, Sundays and public holidays are used in order to calculate the difference between Sunday and Monday as well as the difference between the public holiday and the next day. For each variable 6,544 observations are included in the time series (from January 4th 1983 to May 31st 2008).

Temperature

Table 2 shows descriptive statistics for the first difference weather data. For temperature, the average difference between two days is 1.49 degrees Celsius. For the same reason that applies to the unprocessed data, namely that these outcomes are influenced by seasonality, the standard deviation is very high with 12.3 degrees Celsius. The maximum change in daily mean temperature from one day to another is 9.7 degrees Celsius.

Precipitation

The average difference in precipitation amount between one day and another is 2.93 millimeters. Here the standard deviation heavily exceeds the mean with 4.91 millimeters, which is also caused by seasonality effects. The highest difference in precipitation amount between two days is 56.7 millimeters.

Cloud cover

For cloud cover, the average daily change is 1.6 octants, with another high standard deviation of 1.4 octants. The greatest change in cloud cover between two days is eight octants, but this situation only appears once, on February 13th 2008, in the whole time series.

Humidity

Finally, the mean difference in average observed daily mean relative atmospheric humidity is 6.0%, where the standard deviation is 5.0%, and thus again very high for the previous mentioned reasons. The highest measured difference in humidity from one day to another is 37%.

Based on the positive skewness numbers and on the values of the Kolmogorov-Smirnov tests, one may conclude that deseasonalized first difference weather data are non-normal distributed. However, when examining the histograms in figures 5 to 8 one cannot conclude other than that these first difference weather data are normally distributed.

Seasonality – difference in relation to monthly averages (SA data)

The third type of weather data is the calculated difference on one day in relation to the mean number of the same month (SA). This study used this method to deseasonalize the weather data to control for the fact that all weather variables are highly affected by seasonality. For example, winter months are associated with lower temperatures and more cloudiness in the Netherlands. With this method, this research generates a measurement of a particular day's weather relative to the average seasonal weather, which captures the 'unexpected' component of that day's weather change. Results will then be driven by the weather rather than by other seasonal effects.

In order to deseasonalize the weather data, this study uses a manner similar to Hirschleifer and Shumway (2002) and Goetzmann and Zhu (2002). First, a monthly average for each weather variable, including all days of the month, is computed in order to obtain the deseasonalized data. Then, the average weather variables over time are found by computing the mean of all 25 yearly observations. Table 6 shows the seasonal patterns for all four weather variables. Finally, for all four variables each month's mean is subtracted from each daily mean in order to find the daily seasonally adjusted (SA) weather data.

Temperature

Table 3 presents descriptive statistics for the deseasonalized weather variables. For temperature, the mean deviation from the monthly average is 2.63 degrees Celsius. The standard deviation again is high with 2.04 degrees Celsius. The highest observed difference in temperature in relation to the mean of the month is 16.0 degrees Celsius.

Precipitation

The average difference in amount of precipitation in relation to monthly means is 3.02 millimeters. In addition, the standard deviation is 3.57 millimeters, which is a higher number than the mean. Within the 1983-2008 period, the maximum deviation from a monthly average is 54.2 millimeters, observed on July 4th 2005.

Cloud cover

Concerning cloud cover, the average daily deviation from the monthly average is 1.7 octants, with another high standard deviation of 1.2 octants. The greatest difference in daily cloud cover in relation to the mean of the month is six octants.

Humidity

Finally, the mean difference in average observed daily mean relative atmospheric humidity and the calculated monthly humidity is 6.6%, where the standard deviation is 5.4%, which is very high. The highest measured difference in seasonally adjusted humidity is 40%.

Based on the positive skewness numbers and on the values of the Kolmogorov-Smirnov tests, deseasonalized weather data are non-normal distributed. However, considering the histograms in figures 9 to 12, deseasonalized temperature and humidity data are normally distributed. Deseasonalized precipitation and cloud cover are not normally distributed. Finally, for this type of weather variables, the high standard deviations indicate that the weather in Amsterdam is very diverse and changes from day to day and from week to week.

3.3.4 Computation of ‘extreme change of weather days’ (EW)

For several reasons, it is interesting to investigate whether days with an extreme change of weather, either in relation to the previous day or in relation to the monthly averages, have an effect on AEX returns besides measuring the effect of exclusively the three types of weather variables as described above. First, an investigation like this is the first one of its kind as none of the previous made studies on the influence of weather on financial markets considers this. Furthermore, as this research hypothesizes that the weather has a severe effect on returns of either AEX or one of the three mentioned firms, a consecutive hypothesis is that days on which the weather is very different in relation to either the previous day or the current season should have an even greater influence on returns.

In order to indicate a day as ‘extreme change of weather day’ (EW) seven weather variables are used: daily mean temperature, sunshine duration in 0.1 hour, percentage of maximum possible sunshine duration, precipitation duration in 0.1 hour, precipitation amount in 0.1 mm, cloud cover in octants, and relative atmospheric humidity in percents. For each weather variable, I chose a criterion that measures whether an observed weather observation is an extreme observation or is not. These criteria are expressed in table 7. Finally, when on one particular day four or more criteria are met, this day is marked as ‘extreme change of weather day'. In total, 1518 'extreme change of weather days' in relation to the previous day are found, which is approximately 22.9% of all days within the time series. In addition, 2421 'extreme change of weather days' in relation to the mean of the month of the year are observed, which equals 36.5% of all days.

Just as for the three other types of weather data, this research first examines the influence of extreme weather on Ahold, Heineken and Unilever returns. If this study finds any extreme weather effect on the returns of one or more of these firms, it is necessary to control for this influence when investigating the extreme weather effect on AEX returns.

3.4 Summary

In order to investigate whether the weather in the Netherlands influences the investment climate of the Amsterdam Stock Exchange, this study considers four weather variables: cloud cover, humidity, precipitation and temperature. For the period January 3rd 1983 to May 30th 2008 daily weather data are obtained from the KNMI and subsequently Saturdays, Sundays and other non-trading days are removed from the time series. This study uses three types of weather data, being unprocessed data, (deseasonalized) changes from the previous day's weather data, and (deseasonalized) difference from monthly averages data. This research also observes which days can be indicated as 'extreme change of weather days' either in relation to the previous day or the averages of the month.

AEX index price data for the above-mentioned period are retrieved from DataStream and after this transformed to logarithmic returns. Before examining if the weather influences AEX returns, returns from three other listed firms are investigated in this study, namely those of Ahold, Heineken, and Unilever. As these firms operate in a market with food and beverage products this study hypothesizes that these firms are most affected by the state of the weather. If the weather influences one or more of these firms significantly, it is necessary to control for this effect when examining AEX returns. Ahold shows to most volatility over time, while Unilever shows the smoothest performance curve.

Chapter 4: Results

4.1 Introduction

In order to test the following hypotheses, an ordinary least squares (OLS) regression model is used.

H_0 : the condition of the weather in Amsterdam does not have an effect on investment behavior and therefore the variance in AEX returns does not differ significantly from zero.

H_1 : extreme weather conditions in Amsterdam do not have an effect on investment behavior and therefore the variance in AEX returns does not differ significantly from zero.

This chapter is organized as follows: first, the OLS regression framework is discussed followed by the model specification procedure, which includes tests for stationarity, multicollinearity, autocorrelation and heteroskedasticity. Finally, regression results are presented.

4.2 OLS regression framework

"Regression analysis is an attempt to explain movements in a variable (the dependent variable) by reference to movements in one or more other variables (the independent variables)" (Brooks, 2002). The dependent variable in the regression equation is modeled as a function of all independent variables and a random disturbance (or error) term. This disturbance term is included as it represents unexplained variation in the dependent variable that cannot be modeled (e.g. a hurricane or terrorist attack). The following shows a simple multiple OLS regression equation:

(5) $$Y_i = \beta_0 + \beta_1 X_{1i} + \ldots + \beta_p X_{pi} + \varepsilon_i$$

where Y_i is the dependent variable; X_i are the independent variables; β_0 represents the intercept; β the slope and ε_i is the error term.

This equation can only tell something about the relationship between the dependent and its independent variables if the following regression assumptions are satisfied:

- The assumption of correct functional form: for any value of x, the error is on average zero;
- The constant variance assumption: for any value of x, the error has the same variance;
- The normality assumption: for any value of x, the error is a draw from a normal distribution;
- The independence assumption: each error is statistically independent from any other error.

Even though this study found some evidence for non-normality for some variables in the data set, this study stuck with an Ordinary Least Squares (OLS) regression framework. Brooks (2002): "for sample sizes that are sufficiently large, violation of the normality assumption is virtually inconsequential. Appealing to a central limit theorem, the test statistics will asymptotically follow the appropriate distributions even in the absence of error normality".

In total this study used 20 regression models in the form of equation 5, with four different dependent variables, being returns of AEX, Ahold, Heineken, and Unilever.

For all regression models, this research depicts statistical significance by the F-ratio, which is calculated using the following formula:

(6) $$F = \frac{R^2 / p}{(1-R^2)/(n-(p+1))}$$

where R^2 is a measure of how much of the variability in the outcome is accounted for by the independent variables; p is the number of independent variables and n is the number of observations. The point is to obtain the highest possible F-ratio, as the larger is the F-ratio, the more useful is the model. However, the F statistics will be considered statistically significant or not at a critical value of 10%. In order to test whether each independent variable is statistically different from zero and thus making a significant contribution to the model, this study calculated t-statistics using the following equation:

(7) $$t = \frac{B_{observed}}{Std.Error_B}$$

where the value of B estimates the relationship between the dependent and the independent variable. The point for this statistic also is to obtain the highest possible t-ratio, as the higher is the t-value, the more useful is the independent variable. Just as for the F statistic described above, the critical value for the t statistic to become significant is 10%.

4.3 Model specification procedure

4.3.1 Augmented Dickey-Fuller test for non-stationarity

Before running any regression, it is necessary to test all time series on non-stationarity. A stationary process can be defined as a stochastic process whose joint probability distribution remains the same as time progresses. Because of this, parameters such as the mean and variance do not change over time. If a variable contains a unit root (i.e. is non-stationary), "it can be proved that the standard assumptions for asymptotic analysis will not be valid". More concrete, this means that t-ratios and F-statistics will not follow a normal t-distribution or F-distribution, and therefore it is not possible to draw proper conclusions from the regression outcomes. Also, the stationarity or otherwise of a time series can strongly influence its behavior and properties. A shock, for example, will gradually die away in a stationary dataset, but when the data contains a unit root, the persistence of shocks will be infinite. Finally, when non-stationary data are used in a regression, spurious regressions might originate. A spurious regression could lead to wrong conclusions as it causes high R^2's even if the variables are totally unrelated.

In order to test for non-stationarity in time series data, this study applies the Augmented Dickey-Fuller test. Dickey and Fuller (1979) consider three different regression equations that can be used to detect a unit root in time series data:

(i) $\Delta Y_t = \delta Y_{t-1} + u_t$ for a unit root with random walk

(ii) $\Delta Y_t = a_0 + \delta Y_{t-1} + u_t$ for a unit root with drift

(iii) $\Delta Y_t = a_0 + a_1 t + \delta Y_{t-1} + u_t$ for a unit root with drift and deterministic time trend

The ADF test used in this study is a general version of the model that includes all three forms of unit root, as well as lag terms. The optimal lag length of the ADF test is determined by minimizing the Schwarz (1978) information criterion (SIC). SIC, often also called Bayesian information criterion, is calculated with the following equation:

$$SIC(k) = n\ln(RSS/n) + k\ln(n) \qquad (8)$$

where n is the total number of observation; RSS is the residual sum of squares of the estimated model and k is the number of regressors, including the constant. However, this equation only works under the assumption that the model errors are normally and independently distributed. Usually, SIC is considered as more consistent than other information criteria, such as the Akaike information criterion.

The ADF statistic, the outcome of the test, is always a negative number. The more negative it is, the stronger is the rejection of the hypothesis that the time series is non-stationary. Table 9 presents results of the Augmented Dickey-Fuller test on both return and weather data. The table shows that none of the time series in this study contain a unit root with a confidence interval of 99%, so non-stationarity is not a problem in this study.

4.3.2 Multicollinearity

In statistics bivariate correlation (usually measured as correlation coefficient) indicates the strength and direction of a linear relationship between two variables. Generally, correlation refers to the departure of two variables from independence in relation to the other. When a strong correlation between two independent variables is present in a regression, multicollinearity exists. The best-known measure to test for bivariate correlation between two variables is the Pearson product-moment correlation coefficient (or simply Pearson correlation coefficient). One of the features of this test is that it assumes linearity and a normal distribution of both variables. The coefficient is obtained by dividing the covariance of both variables in the test by the product of their standard deviations:

$$r = \frac{\mathrm{cov}_{xy}}{s_x s_y} = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{(N-1) s_x s_y} \tag{9}$$

When calculating this correlation coefficient, the value will always lie between -1 and +1. A coefficient of -1 indicates a perfect negative relationship, which means that if one variable decreases the other one increases by a proportionate amount. A coefficient of +1, on the other hand, indicates a perfect positive relationship, which works oppositely to the -1 coefficient. This research considers a correlation coefficient equal to or smaller than (-).15 as a small correlation; a coefficient between (-).15 and (-).50 as a medium correlation and a coefficient equal to or larger than (-).50 as a large correlation. In order to use variables in a regression, two independent variables with a high correlation coefficient are not useful because high levels of collinearity increase the probability that a good predictor of the outcome will be non-significant and therefore rejected from the model. Besides, multicollinearity limits the R (a measure of the multiple correlation between the independent variables and the outcome) and makes it difficult to assess the individual importance of the independent variables. For these reasons, when two variables are found to have a large correlation, one of them needs to be removed from the regression.

Tables 10 to 13 present four correlation matrices that show the correlation coefficients of the AEX, Ahold, Heineken, and Unilever returns; of the unprocessed weather variables; of the first difference weather variables and of the difference in relation to monthly averages weather data. Table 10 shows that the returns of Ahold, Heineken and Unilever are all medium correlated with the AEX index returns. This result is not very surprising as the AEX index returns are partly based on the returns of these three companies. What is more surprising, is that Unilever's returns are, of these three, the ones that are least correlated with the index returns despite the fact that Unilever has a far higher index weighting (8.35%) than both Ahold and Heineken (2.70% and 2.23%, respectively).

When examining the correlation coefficients of the unprocessed weather data in table 11, it immediately appears that cloud cover and humidity are highly correlated (0.57) which means that when there are more clouds in the sky, the atmosphere becomes more humid. Temperature and precipitation are almost uncorrelated, indicating that the amount of rain in the Netherlands does not really changes if the air gets warmer or colder.

Table 12 presents the next correlation matrix for first difference weather data. Again, a high correlation coefficient is found between cloud cover and humidity (0.48), though for this type of weather data no real correlation problems are detected. For the deseasonalized weather data presented in table 13, this research finds that cloud cover and humidity are highly correlated with a coefficient of 0.55.

4.3.3 Durbin-Watson test for serial correlation

Once the regression models are constructed, the next step is to test for both serial correlation and heteroskedasticity. Serial correlation (also known as autocorrelation or cross-correlation) can be described as the correlation between different observations of one variable as a function of the time separation between them. In a regression study, it is preferable not to have autocorrelation in data. In other words, for any two observations of one variable the residual terms should be independent (uncorrelated). Durbin and Watson (1951) developed the following measure to test for the assumption that serial correlation is not present in data:

$$DW = \frac{\sum_{t=2}^{T} (\hat{u}_t - \hat{u}_{t-1})^2}{\sum_{t=2}^{T} \hat{u}_t^2} \qquad (10)$$

The denominator of this equation is simply (the number of observations -1) x the variance of the residuals, while the numerator compares the error values at times t-1 and t. The outcome of this test will always lie between 0 and 4, where a value of 2 indicates zero autocorrelation. A value below 2 indicates a negative serial correlation, while a value above 2 indicates a positive autocorrelation. This study assumes that Durbin-Watson statistics lower than 1.46 and higher than 2.37 indicate serial correlation (critical values at the 1% level, based on Econometrica, 1980 with four independent variables and a maximum of 100 observations).
Tables 15 to 30 present results of the Durbin-Watson tests. As all of the reported values are close to two and lie in the range 1.46-2.37, one can conclude that autocorrelation is not a problem in this research.

4.3.4 White test for heteroskedasticity

Heteroskedasticity ("differing variables") is defined as the random variables of a data set having different variances. The opposite concept is called homoskedasticity. To recall, one of the assumptions of an OLS regression model is that the error has a constant variance. Heteroskedasticity violates that assumption and therefore is not preferred in the regression models used in this study. White (1980) developed a widely used measure to test for heteroskedasticity in data. This test regresses the squared residuals from a regression model onto the regressors, the cross products of the regressors and the squared regressors. Finally, the test statistic is the product of the R^2 and the sample size (also called the Lagrange Multiplier). Tables 15 to 30 present R^2s for the regression models used in this study. As all R^2s are low with values of 0.000 or 0.001, subsequently the resulting test statistics also are low. In all cases, the test statistics stay under the corresponding 5% critical values, so one can conclude that heteroskedasticity is not a problem in this study.

4.4 Results

4.4.1 Unprocessed weather data

As three different types of weather data are distinguished, also three different regression models are constructed. These regressions take the following form:

$$R_i = \beta_0 + \beta_1 CK_i + \beta_2 HUM_i + \beta_3 PREC_i + \beta_4 TEM_i + \varepsilon_i \tag{11}$$

Where, for unprocessed weather data, R_i is the log return from either the AEX, Ahold, Heineken or Unilever; β_0 is the intercept; $\beta_1 CK_i$ denotes cloud cover; $\beta_2 HUM_i$ denotes humidity; $\beta_3 PREC_i$ denotes precipitation; $\beta_4 TEM_i$ denotes temperature and ε_i is the error term. However, as this study previously found a serious correlation between cloud cover and humidity for UP weather data, either humidity or cloud cover (the one having the lowest explanatory power) will be excluded from the regression. In order to find which variable has the lowest explanatory power, this study first ran single regressions of the following form for all four weather variables:

(12) $$R_i = \beta_0 + \beta_1 X_{1i} + \varepsilon_i$$

where R_i again is the log return from AEX, Ahold, Heineken or Unilever and X denotes the particular weather variable at hand (cloud cover, humidity, precipitation or temperature). Results of these single UP regressions for AEX returns are found in table 14 (results of the other single regressions can be found in the tables section of the appendix).

Ahold returns

In order to find whether unprocessed weather variables are of any influence on the returns of Ahold, a food retailer and wholesaler, this study used the following manner. First, as cloud cover is less significant than humidity for unprocessed weather data (a significance level of 0.628 against 0.645, respectively), this research excluded cloud cover from the regression model with Ahold returns. Subsequently, a hierarchical three-step regression model was constructed, where first solely the variable with the highest explanatory power is included, subsequently the one with the next highest explanatory power is added, and finally the one with the lowest explanatory power is added:

(i) $$R_i = \beta_0 + \beta_1 PREC_i + \varepsilon_i$$

(ii) $$R_i = \beta_0 + \beta_1 PREC_i + \beta_2 HUM_i + \varepsilon_i$$

(iii) $$R_i = \beta_0 + \beta_1 PREC_i + \beta_2 HUM_i + \beta_3 TEM_i + \varepsilon_i$$

Table 16 shows the regression results of this three-step UP regression model for Ahold returns. In the column labeled R the values of the multiple correlation coefficient between the independent variables and the outcome are presented. For example, the value of R for model three in table 16, 0.010, means that the three included independents together – precipitation, humidity, and temperature – show a correlation coefficient of 0.010 with the Ahold log returns, which is very low. Besides, the values of R for model one and two in tables 16 are even lower (0.006 and 0.010, respectively). The values in the R^2 column present a measure of how much of the variability in the outcome is accounted for by the independent variables in the model. Together, the weather variables in this model explain 0.00% of the variance in AEX log returns. Considering the F statistics, one can see that the first model, where only precipitation is included, shows the highest significance (60.4% against 71.4% and 87.9% for model two and three, respectively) and thus is the best model of these three. However, none of these models is close to statistically significance. The coefficients for Ahold returns are very low with, for instance, -0.0000014 for precipitation in the first model. This number indicates that, on a particular day, when the precipitation in Amsterdam increases with one millimeter, the Ahold return on that day decreases with 0.0000014 Euros. When examining the t values, one finds the same results as for the F values; none of them is significant. One can only retain the hypothesis that unprocessed weather does not influence returns of Ahold.

Heineken returns

This study used a similar mode of operation for the regression model with unprocessed weather variables as regressors and log returns of Heineken as regressand, as presented in table 17. One can see that the first model, where solely humidity is included, is the best one as it is the only one with a significant F statistic of 8.4%. R (0.021, 0.025, and 0.026) and R^2 (0.000, 0.001, and 0.001) values for all three models are, again, very low. Likewise the coefficients of the independent variables are, with the only one significant being humidity in model one, low. The humidity coefficient in model one is -0.000015 that indicates that when on a particular day the relative humidity increases with 1%, the log return of Heineken decreases with 0.000015 dollar on that same day. The t value of this coefficient is with -1.731 statistically significant with 8.4%. However, again one can conclude that the unprocessed weather variables in this study do not affect Heineken stock returns.

Unilever returns

Examining the next model in this study where log returns of Unilever are the dependent variable, presented in table 18, one can see that the first model where only one independent variable is included is the best model. Even though the R^2 is 0.000, the F value of 3.250 in this model has a significance value of 7.1%. None of the other two models is significant. The temperature coefficient in model one is -0.0000027, which indicates that when the temperature increases with one degree Celsius, the return of Unilever decreases with 0.0000027 dollar, which is a negligible result. One more time, one can conclude, with the low

R's, R^2s, and coeffients that unprocessed weather variables do not influence log returns of Unilever.

AEX returns

Having discovered that Ahold, Heineken, or Unilever returns are not significantly influenced by the weather, there is no need to find a way to control for the weather influence on these firms within the AEX returns regressions. The single UP regressions in table 14 show that humidity is less significant than precipitation (a significance level of 0.890 against 0.811, respectively). Therefore, this research excluded humidity from the regression model with AEX returns. Table 15 presents regression results for unprocessed weather variables and AEX returns. One can observe that the R^2 values are very low, being 0.001 for all three regressions. As this implies that the weather variables in this model together only explain 0.1% of the variance in AEX log returns, one can already conclude that unprocessed weather variables do not have any influence on AEX returns. However, in this model temperature alone explains 0.1% of the variance in AEX returns, which already indicates that both cloud cover and precipitation do not significantly influence AEX returns. Considering the F statistics, one can see that the second model, where temperature and cloud cover are included, shows the highest significance (2.7% against 5.7% and 5.9% for model one and three, respectively) and thus is the best model of these three. One can also see this in the significance of the t values for the different models. Model two shows significant t values for both variables (temperature 3.2% and cloud cover 5.8%). However, the coefficients are quite low with -0.00000240 for temperature and -0.00006100 for cloud cover. These numbers indicate that, on a particular day, when the temperature in Amsterdam increases with one degree Celsius, the AEX return on that day decreases with 0.0000024 Euros. One can conclude that this is somewhat surprising as I hypothesized that better weather (less clouds, lower humidity, less precipitation, and higher temperature) improves investor's optimism and therefore improves returns. When cloud cover increases with one octant (when it becomes less 'sunny') the AEX return on that same day decreases with 0.000061 units. Yet, as the R^2 and these coefficients are so low, one can only conclude that unprocessed weather does not influence AEX log returns.

4.4.2 First difference weather data

The regression models for first difference weather data are constructed in a similar routine as the regression models for the unprocessed weather data. However, as this study did not find any serious correlations between the four weather variables for first difference weather data, all four weather variables are included in the hierarchical regression model.

Ahold returns

Table 20 presents first difference weather regression results with Ahold returns as regressand. None of the four regressions in the hierarchical model is statistically significant. The R's are very low with 0.013, 0.014, 0.014 and 0.014 as well as the R^2's with a value of 0.000 for all four regressions. The R values show that temperature alone explains most of the correlation (0.013 out of 0.014) with the dependent variable Ahold returns. Next to that, the second variable precipitation also explains a very small part of the correlation (0.001 out of 0.014). All of the resulting coefficients in this regression model show very low numbers and next to that, none of them shows significant t values. One can conclude that weather, deseasonalized in the form of the difference between one day and the previous day, does not have any influence on the variance in returns of Ahold.

Heineken returns

Table 21 presents a regression model that regressed the four weather variables, deseasonalized in the form of the difference between one day and the previous day, with the log returns of Heineken. One can see that the R values are very low with 0.011, 0.015, 0.017 and 0.018 as well as the R^2's with four times 0.000. Having examined the F statistics, one can also see that none of the regression models is close to statistically significance. All of the coefficients are very low and none of the t values is significant. One can conclude now that deseasonalized first difference weather variables do not affect investment behavior and therefore do not affect returns of Heineken.

Unilever returns

Table 22 presents the resulting regression model with Unilever returns as response variable and deseasonalized first difference weather variables as predictors. The resulting R values in this section are low with 0.016, 0.020, 0.020 and 0.021. Besides, the R^2 values do not exceed 0.000 and thus one can consider these very low. In this case, none of the variance in Unilever log returns is explained by a combination of the temperature, precipitation, humidity, and cloud cover of one particular day in relation the temperature, precipitation, humidity, and cloud cover the day before that particular day. Just as in all the examined regression models above, the coefficients in this model are very close to zero and none of their t values are statistically significant. One needs to conclude that the four deseasonalized first difference weather variables do not have any influence on the variance in returns of Unilever.

AEX returns

Having discovered that Ahold, Heineken, or Unilever returns are not significantly influenced by the weather when first difference weather variables are taken, there is no need to find a way to control for the weather influence on these firms within the AEX returns regressions.
Table 19 presents regression results for a model with AEX returns as dependent variable and all four weather variables as independents. One can see that the first model, where only temperature is included in the regression, is the only model significant with an F statistics of 2.978 and a significance level of 8.4%. However, when examining the R^2, the coefficient and the t statistic, one can see that none of these values shows any first difference weather effect on AEX returns. The R^2 results in 0.000 and the coefficient of 0.00000606 shows that, on a particular day, when temperature increases with 1 degree Celsius, the return of AEX increases with 0.00000606 on that same day, which is again a negligible increase. As this study already found a negative relationship between temperature and AEX returns (for unprocessed weather data), this result might indicate that a spurious relationship between weather and returns is present.

4.4.3 Difference in relation to monthly averages weather data

This research has already concluded that both unprocessed weather variables and deseasonalized first difference weather variables did not influence returns of the AEX index during the past 25 years. In addition, no weather effect is found when returns of either Ahold, Heineken or Unilever are used as dependent variable in the regression. A final method in this study to analyze if the weather in Amsterdam has any influence on returns of the AEX index, Ahold, Heineken or Unilever, is to use deseasonalized weather data in the form of the difference between a particular day's cloud cover, humidity, precipitation, or temperature and the calculated monthly average cloud cover, humidity, precipitation, or temperature. For this type of weather data, a similar hierarchical regression methodology is used as above.

However, as for this weather type a strong correlation is found between cloud cover and humidity, the one with the lowest explanatory power of these two is excluded from the model.

Ahold returns

Table 24 presents results from a regression that should show if any relationship is presents between deseasonalized - in the form of weather differences in relation to monthly averages - precipitation, humidity, and temperature and Ahold log returns. This table shows very low R values as well as R^2 values. Furthermore, the F values are very low and none of them is statistically significant. The presented coefficients in this model also do not show any weather effect as they show numbers very close to zero and t values that are not even close to statistically significance. One needs to conclude that also this regression model does not shows any weather effect.

Heineken returns

The subsequent step in study was to regress deseasonalized, in relation to monthly means, weather with log returns of Heineken. Table 25 presents the results. This table reveals that this time humidity is the weather variable with the most explanatory power as if explains most of the correlation coefficient R (0.027 out of 0.029). Where precipitation explains the remaining 0.002, temperature does not explain anything of the correlation coefficient with returns of Heineken in this model. One can see that the F statistics are significant for both the first and second regression with 2.8% and 6.1%. However, the coefficients show very low numbers with -0.000019 and -0.0000016 in the second model. These numbers indicate that when humidity increases with one percent, the return of Heineken decreases with 0.000019 dollars. In addition, when precipitation increases with one millimeter, the return of Heineken decreases with 0.0000016. This again might be a sign that spurious relations are presents within this study. Anyhow, one needs to conclude that these results do not indicate any weather effect on Heineken returns.

Unilever returns

Table 26 presents a penultimate regression model of this kind. It includes Unilever returns as dependent variable, and temperature, humidity, and precipitation as independent variables. One can see that only the first model, where solely temperature is included, is statistically significant with 4.1%. Temperature is the variable here that explains the most severe part of the correlation coefficient R. When examining the values of the coefficients, one can see that these are again very close to zero and consequently do not indicate any weather influence on returns of Unilever. The t values again show that temperature is the variable with the most explanatory power in this model as it is the only one significant. One can only conclude that there was no weather effect on Unilever returns present during the past 25 years.

AEX returns

Having discovered that Ahold, Heineken, or Unilever returns are not significantly influenced by the weather when differences from monthly average weather variables are examined, there is no need to find a way to control for the weather influence on these firms within the AEX returns regressions. Table 23 presents the resulting regression model with cloud cover, precipitation, and temperature as regressors and AEX returns as regressand. One can see that model one and two both show significant F values, though the first one is more significant (3.9% against 9.8%). Considering the R values of 0.025, 0.026 and 0.026, one can see that the this time cloud cover is the variable with the strongest explanatory power as it explains 0.025 of 0.026 of the correlation with AEX returns. Precipitation explains the remaining 0.001. The t statistics within the results of this regression model show a significant value for cloud cover for regression one, two and three. Nevertheless, the cloud cover coefficient in regression two is very low with -0.000074. This number indicates that when cloud cover increases with one octant (when it becomes more ‘sunny’), the AEX return decreases with 0.000074 Euros. The precipitation coefficient is even lower with 0.00000094, which indicates that when the precipitation increases with one millimeter, the AEX increases with 0.00000096. As this study hypothesized that returns improve when weather improves (i.e. when precipitation decreases), this result might be considered surprising. As already mentioned, this might indicate a spurious relationship. However, one cannot conclude that deseasonalized weather is of any influence on the AEX index.

4.4.4 ‘Extreme change of weather days’

Until this point, this study discovered that the three previously described types of weather in Amsterdam do not have any influence on returns of either the AEX index, Ahold, Heineken, or Unilever. A subsequent method in order to test whether the weather in Amsterdam influences returns is to fit a measure of ‘extreme change of weather days’ into a single regression model of the following form:

(13) $$R_i = \beta_0 + \beta EW_i + \varepsilon_i$$

where R_i is the log return from either the AEX, Ahold, Heineken or Unilever; β_0 is the intercept; βEW_i denotes ‘extreme change of weather days’ either in relation to the previous day or in relation to the average of the month and ε_i is the error term.

First, this study investigated the regression results of Ahold, Heineken and Unilever to check for any influence of extreme weather. If an extreme weather effect in the returns of one or more of these firms, it is necessary to control for this effect in the AEX regressions.

Ahold returns

Table 28 presents a model that used Ahold returns as dependent variable. The R values (0.004 and 0.012) are very low, as well as the R^2 values (0.000 and 0.000). When examining the F values one can see that both of them are very low and not significant. In addition, the coefficients do not show values severely different from zero with values of 0.0000971 and 0.000000, so this regression model does not show any influence of extreme weather on the returns of Ahold.

Heineken returns

Table 29 shows the next regression output for Heineken returns as dependent variable. One can immediately see that, in this model, extreme weather conditions do not have any influence on the returns of Heineken as the R (0.009 for both extreme weather measures) and R^2 (0.000 for both extreme weather measures) are very low. Subsequently, the F values in this regression output are not statistically significant. In addition, both coefficients are zero and therefore do not explain anything in the variance of the returns.

Unilever returns

The penultimate regression model in this study shows very similar returns as the previous one does and is presented in table 30. However, this time the regressand is Unilever returns. One can see that the R values are 0.009 and 0.011, which is both very low. In addition, the R^2 values and the coefficients do not exceed zero and therefore do not indicate any influence of extreme Amsterdam weather on the returns of Unilever.

AEX returns

Having discovered that Ahold, Heineken, or Unilever returns are not significantly influenced by extreme weather when differences from monthly average weather variables are examined, there is no need to find a way to control for the weather influence on these firms within the AEX returns regressions. Table 27 presents results for 'extreme change of weather days' in relation to both the previous day and the averages of the particular month regressed with AEX returns. For both types of 'extreme change of weather days' very low R (0.019 and 0.003) and R^2 (both 0.000) values are found. In addition, both F statistics are very low with 2.388 and 0.073 and are naturally not statistically significant. The coefficient for EW days in relation to the averages of the month is very close to zero with 0.000038, though the coefficient for EW days in relation to the previous day is zero. Furthermore, the t values are low and not significant. On can now conclude that, on days where the weather is severely different from the day before or on days that the weather is severely different from the expected weather according to the season, returns of the AEX index are not affected. Naturally, I have to retain to the null hypothesis that, on days where an extreme change of weather is present, AEX returns do not react on this extreme weather.

4.5 Summary

Having first examined if any weather influence is present on three AEX-listed companies – Ahold, Heineken, and Unilever – only one conclusion can be drawn: the weather in Amsterdam does not have any influence on returns of one of these food and beverage products firms. If a particular effect were found, it would have been necessary to control for this effect in examining the weather effect on AEX returns. Having investigated the influence of weather on AEX returns, also only one can conclusion can be drawn: the weather in Amsterdam does not affect investment behavior in the Netherlands and therefore does not affect AEX returns. In addition, when extreme weather conditions are examined, this study did not find any extreme weather effects on Ahold, Heineken, or Unilever returns neither on AEX returns. Regression outputs in this research show very low values for R and R^2. In addition, all coefficients are not economically significant and thus explain nothing of the variance in returns. As already noted before, in almost each regression model another weather variable is the one with the most explanatory power. In addition, for some weather variables sometimes positive and other times negative relations with the dependent variable are found.

Both of these findings point to a present spurious relationship within the data, which implies that the results in this study might be caused by another factor or randomness.

Chapter 5: Summary and conclusion

This paper's primary objective was to investigate if the weather in Amsterdam affects the decision making process of investors and thereby affects financial markets in the Netherlands. This study hypothesized that four parameters might have an effect on investor's choices; the amount of cloud cover, the relative atmospheric humidity, the amount of precipitation, and the temperature in degrees Celsius. This study hypothesized that returns will not change when cloud cover, humidity precipitation, or temperature decreases or increases. Before measuring the effect on returns of the AEX index, the returns on Ahold, Heineken and Unilever are examined. This research chose these three listed companies because I hypothesized that firms in a market with food and beverage might be more influenced by the state of the weather. If this is the case, it is necessary to control for this influence when investigating the influence of the weather on AEX returns. All included datasets in this study range from January 3rd 1983 (the start data of the AEX index) to May 31st 2008. This leads to a period of about 25 years and circa 6550 observations after removing Saturdays and Sundays from the datasets. An additional element of this study was to include a model that measured extreme weather. I calculated which days occurred to have exceptional weather circumstances either in relationship to the day before or to the average of the month.

Having examined the results in this study, one can conclude that no weather effect is present in the Netherlands at all and that thus all hypotheses hold. In addition, there is no stronger effect for both the firms in the markets in food and drinks and on days with exceptional weather conditions. One can conclude now that the weather is not of any influence in order to predict investor behavior in the Netherlands. However, many other factors might have an effect on this behavior in the Netherlands. If one thoroughly wants to study Dutch investor decision making one needs to examine all of these factors. This weather study only explains a small part of the puzzle.

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Figures

Figure 1: Histogram Temperature – Unprocessed data
(January 3rd 1983 – May 30th 2008)

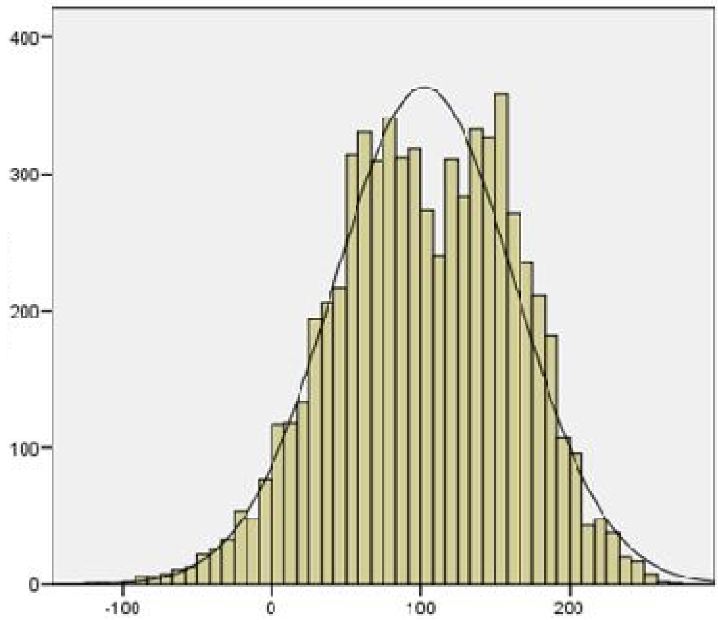


Figure 2: Histogram Precipitation – Unprocessed data
(January 3rd 1983 – May 30th 2008)

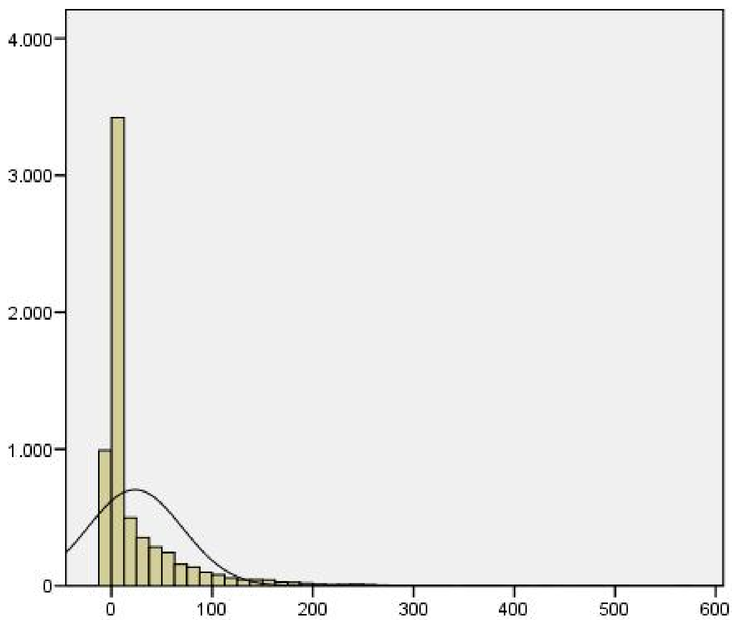


Figure 3: Histogram Cloud cover – Unprocessed data
(January 3rd 1983 – May 30th 2008)

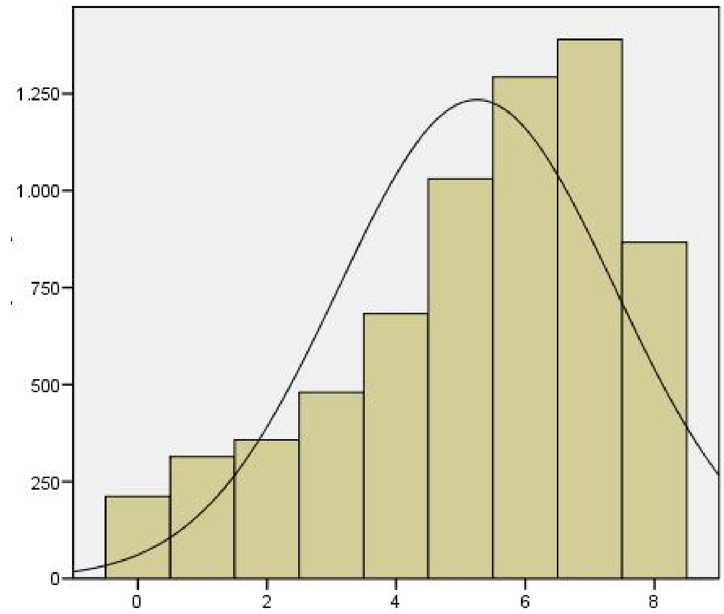


Figure 4: Histogram Humidity – Unprocessed data
(January 3rd 1983 – May 30th 2008)

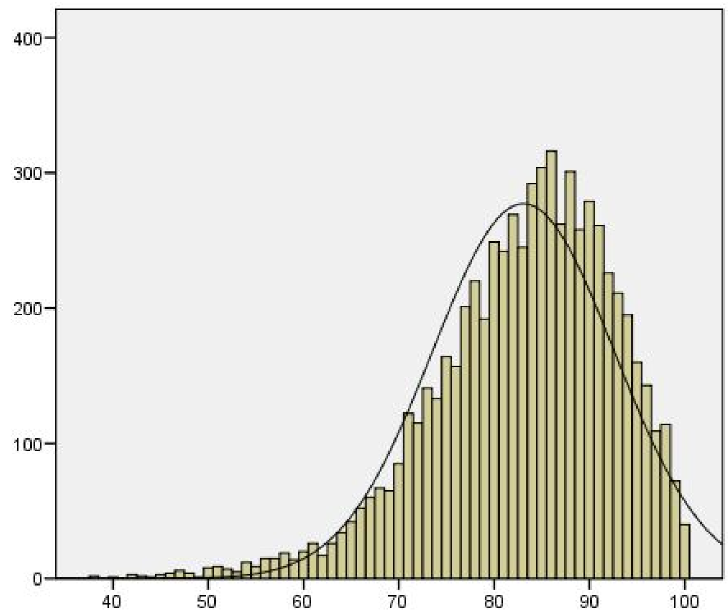


Figure 5: Histogram Temperature – Difference from previous day
(January 3rd 1983 – May 30th 2008)

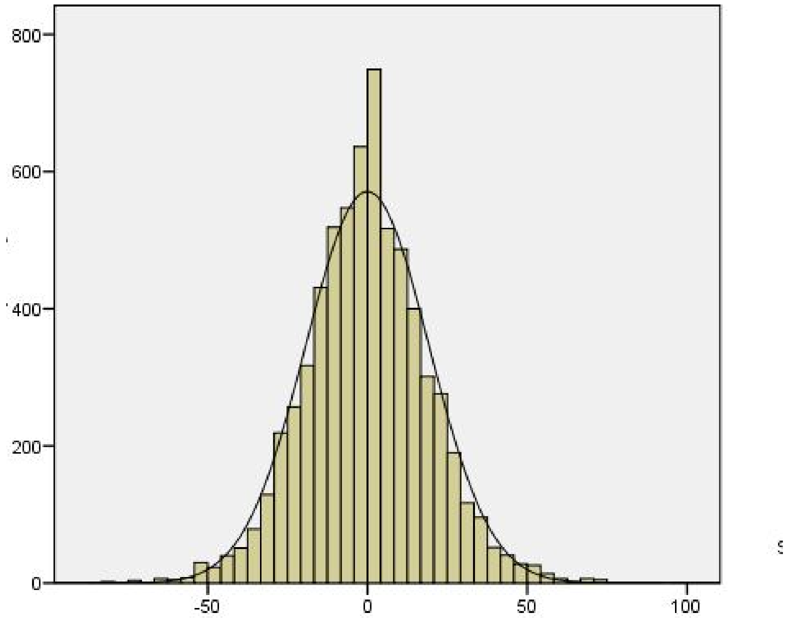


Figure 6: Histogram Precipitation – Difference from previous day
(January 3rd 1983 – May 30th 2008)

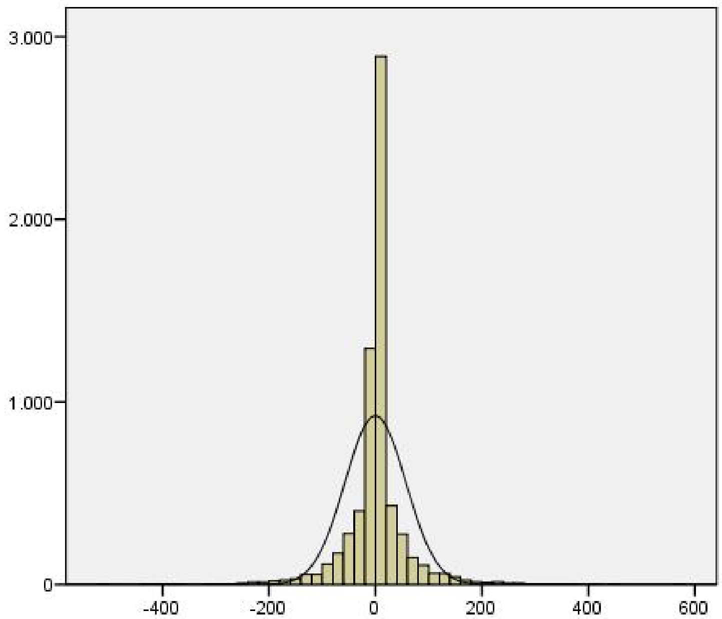


Figure 7: Histogram Cloud cover – Difference from previous day
(January 3rd 1983 – May 30th 2008)

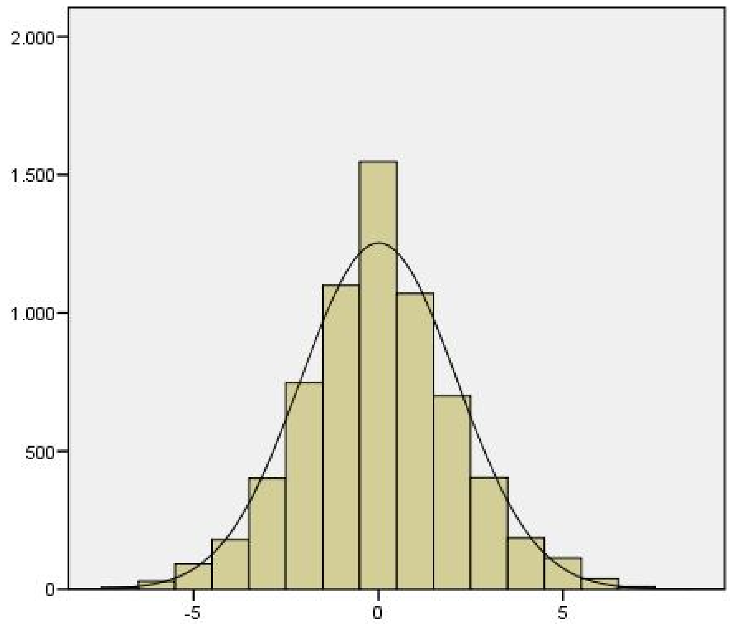


Figure 8: Histogram Humidity – Difference from previous day
(January 3rd 1983 – May 30th 2008)

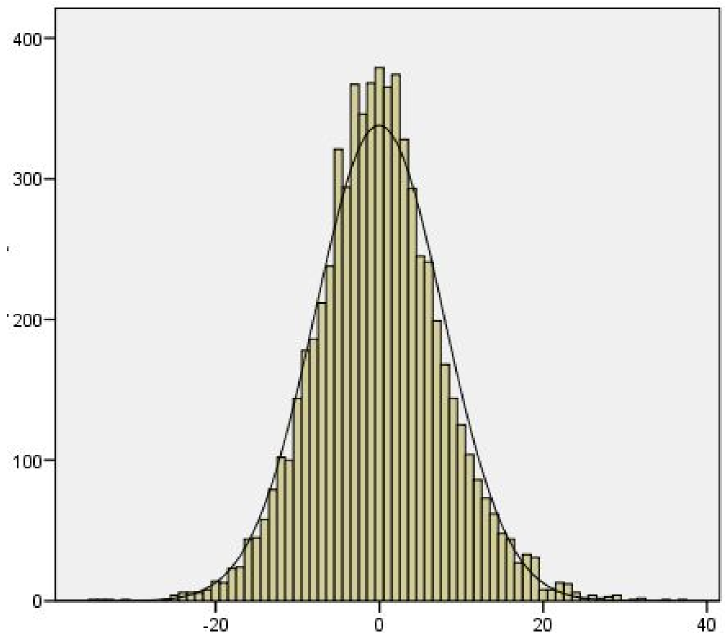


Figure 9: Histogram Temperature – Difference from monthly average (January 3rd 1983 – May 30th 2008)

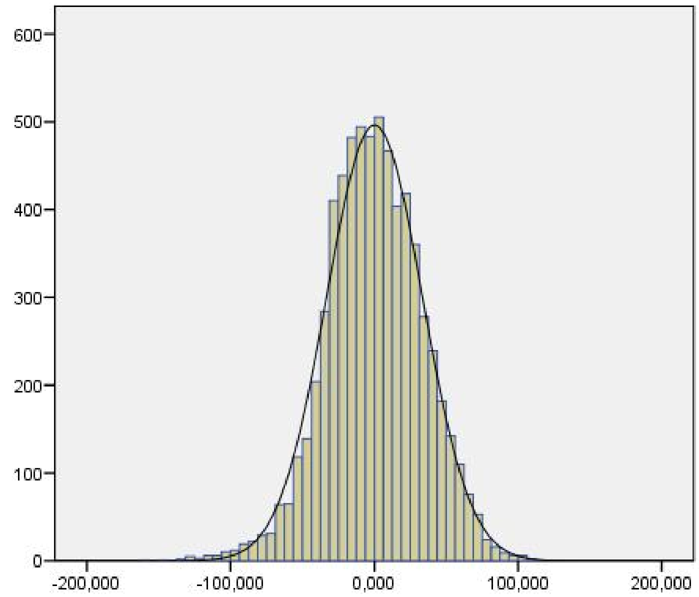


Figure 10: Histogram Precipitation – Difference from monthly average (January 3rd 1983 – May 30th 2008)

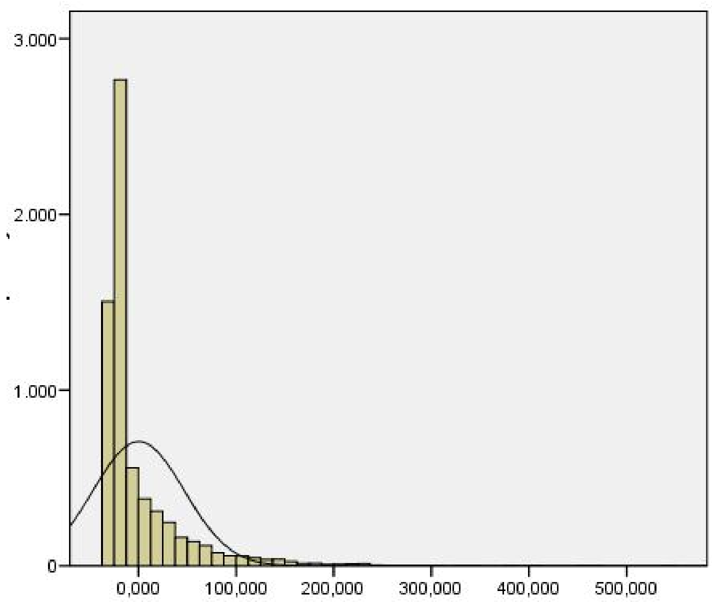


Figure 11: Histogram Cloud Cover – Difference from monthly average
(January 3rd 1983 – May 30th 2008)

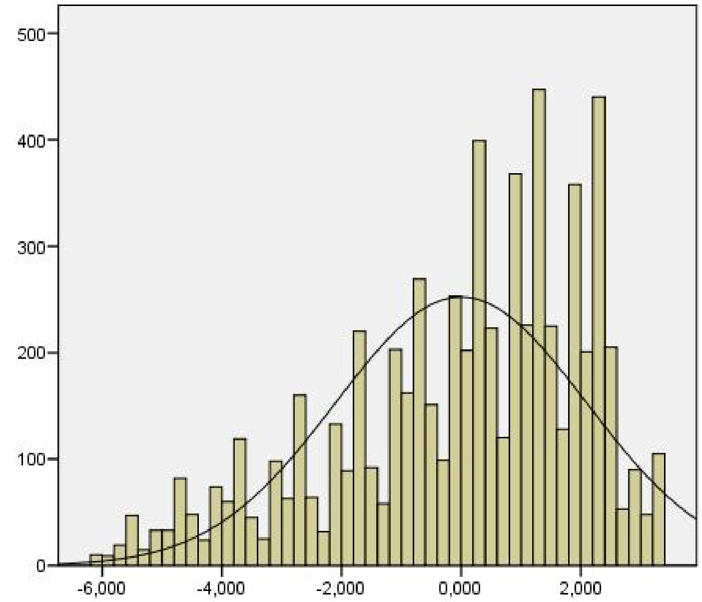


Figure 12: Histogram Humidity – Difference from monthly average
(January 3rd 1983 – May 30th 2008)

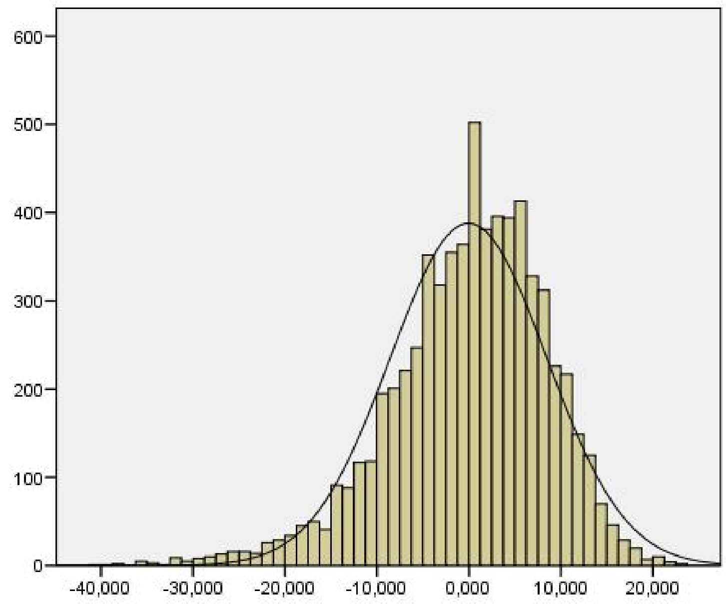


Figure 13: Histogram AEX Log Return
(January 3rd 1983 – May 30th 2008)

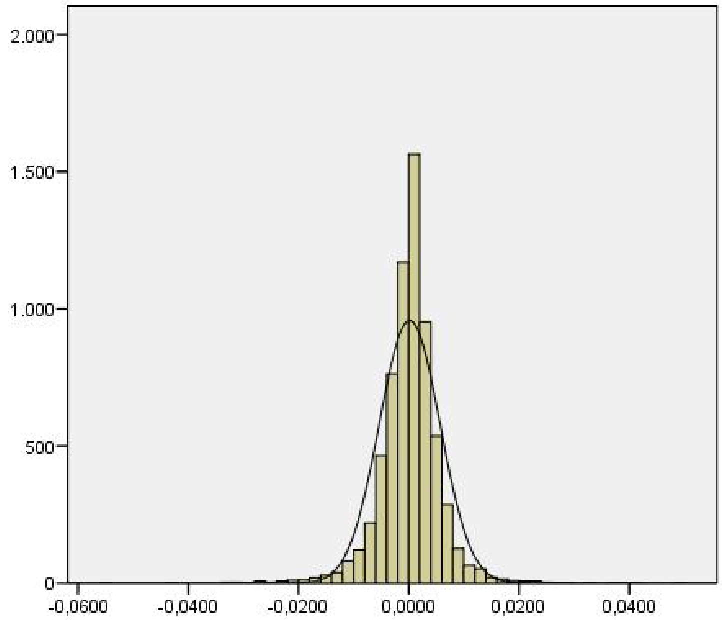


Figure 14: Histogram Ahold Log Return
(January 3rd 1983 – May 30th 2008)

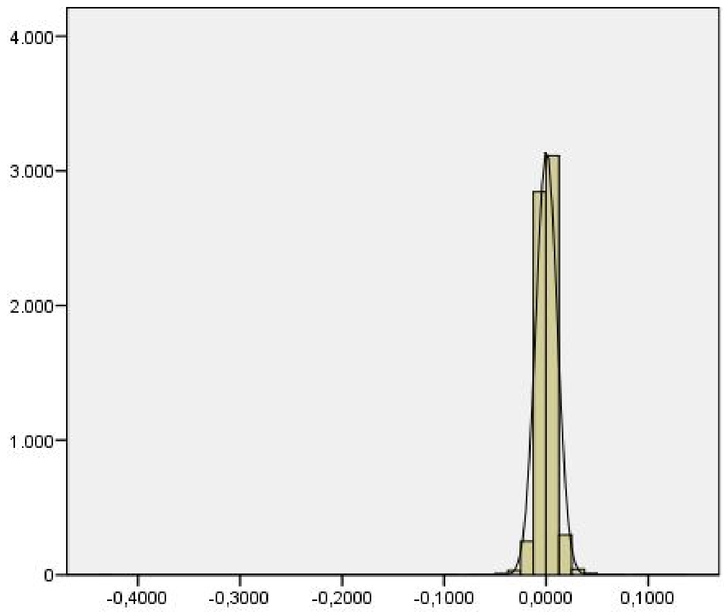


Figure 15: Histogram Heineken Log Return
(January 3rd 1983 – May 30th 2008)

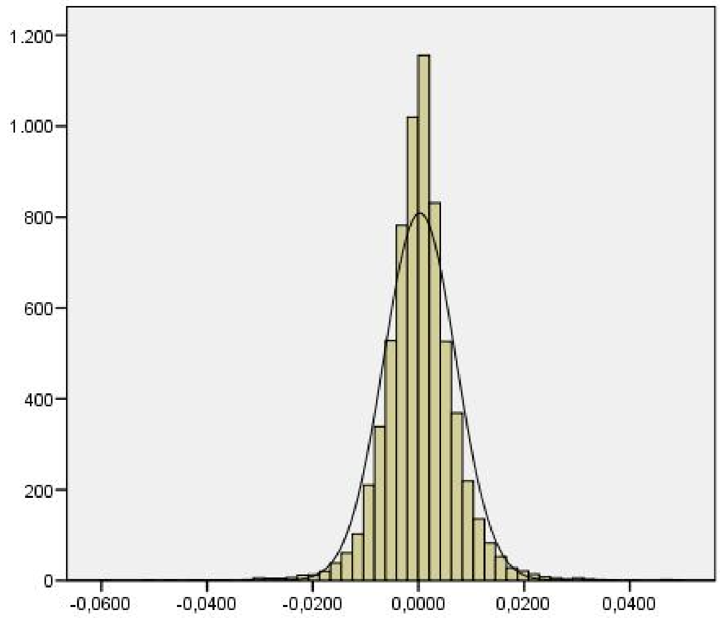
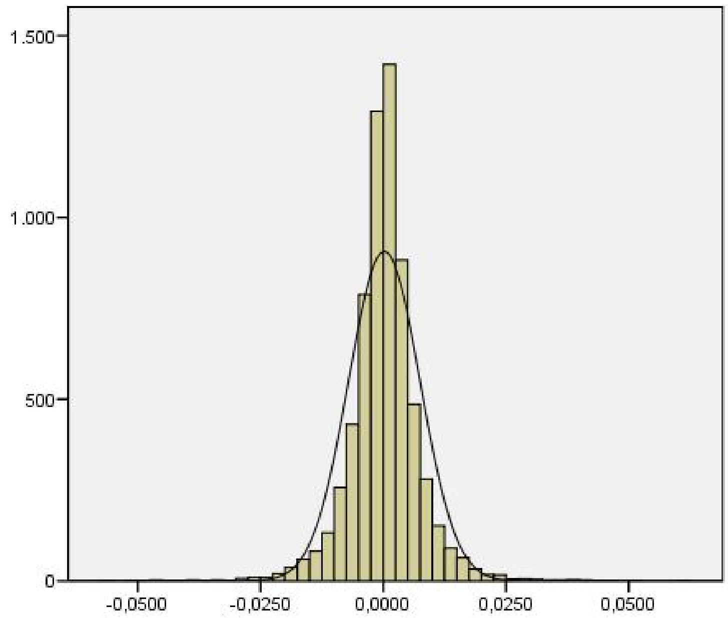


Figure 16: Histogram Unilever Log Return
(January 3rd 1983 – May 30th 2008)



Tables

Table 1: Descriptive statistics for unprocessed weather data
(January 3rd 1983 – May 30th 2008)

Data	Mean	Std. dev.	Min.	Max.	Range	Skewness	Kurtosis	Kolmogorov-Smirnov test of normality* - significance
Daily mean temperature in 0,1 C	102,5	60,7	-123	267	390	-0,19	-0,34	0,000
Daily precipitation amount in 0,1 mm	23,3	47,0	-1	567	568	3,41	16,55	0,000
Cloud cover in octants	5,2	2,1	0	8	8	-0,73	-0,27	0,000
Daily mean relative atmospheric humidity in percents	83,1	9,5	38	100	62	-0,81	0,96	0,000

* with Lilliefors Significance Correction

Table 2: Descriptive statistics for calculated difference from previous day's weather
(January 3rd 1983 – May 30th 2008)

Data	Mean	Std. dev.	Min.	Max.	Range	Skewness	Kurtosis	Kolmogorov-Smirnov test of normality* - significance
Difference in daily mean temperature in 0,1 C	14,9	12,3	0	97	97	0,99	0,81	0,000
Difference in daily precipitation amount in 0,1 mm	29,3	49,1	0	567	567	1,33	2,35	0,000
Difference in cloud cover in octants	1,6	1,4	0	8	8	1,45	2,97	0,000
Difference in daily mean relative atmospheric humidity in percents	6,0	5,0	0	37	37	3,12	14,29	0,000

* with Lilliefors Significance Correction

Table 3: Descriptive statistics for calculated difference from monthly averages
(January 3rd 1983 – May 30th 2008)

Data	Mean	Std. dev.	Min.	Max.	Range	Skewness	Kurtosis	Kolmogorov-Smirnov test of normality* - significance
Difference in daily mean temperature in 0,1 C	26,3	20,4	0	160	160	1,29	2,33	0,000
Difference in daily precipitation amount in 0,1 mm	30,2	35,7	0	542	542	4,79	32,92	0,000
Difference in cloud cover in octants	1,7	1,2	0	6	6	0,96	0,76	0,000
Difference in daily mean relative atmospheric humidity in percents	6,6	5,4	0	40	40	1,53	3,63	0,000

* with Lilliefors Significance Correction

Table 4: Descriptive statistics for log returns of AEX index, Ahold, Heineken, and Unilever
(January 3rd 1983 – May 30th 2008)

Data	Mean	Std. dev.	Min.	Max.	Range	Skewness	Kurtosis	Kolmogorov-Smirnov test of normality* - significance
AEX log return	0,00021	0,00729	-0,057	0,062	0,120	-0,078	7,549	0,000
Ahold log return	0,00031	0,01047	-0,434	0,131	0,564	-9,933	459,226	0,000
Heineken log return	0,00026	0,00680	-0,060	0,049	0,109	-0,041	5,816	0,000
Unilever log return	0,00016	0,00551	-0,055	0,049	0,104	-0,323	8,324	0,000

* with Lilliefors Significance Correction

Table 5: Distribution of Cloud cover octants

Cloud cover in octants	Frequency	Percent	Cumulative Percent
0	212	3,20	3,20
1	314	4,74	7,93
2	357	5,38	13,32
3	480	7,24	20,56
4	684	10,32	30,87
5	1032	15,57	46,44
6	1293	19,50	65,94
7	1390	20,97	86,91
8	868	13,09	100,00
Total	6630	100,00	

Table 6: Seasonal pattern of weather

Month	Temperature in 0.1 C	Precipitation in mm	Cloud cover in octants	Humidity in percents
January	36,7	22,2	5,8	87,9
February	36,2	18,6	5,5	85,2
March	60,7	19,2	5,4	83,4
April	90,6	14,5	4,8	77,9
May	129,9	17,2	4,8	76,5
June	153,4	22,7	5,1	78,7
July	175,2	24,7	4,8	79,9
August	175,0	27,6	4,7	79,9
September	147,0	29,8	5,1	83,7
October	111,4	27,9	5,3	85,9
November	69,7	29,2	5,8	89,1
December	45,0	25,5	6,0	89,5

Table 7: Criteria for 'extreme change of weather days'

Weather variable	Criterion
Daily mean temperature in 0.1 degrees Celcius	> 20
Sunshine duration in 0.1 hour	> 20
Percentage of maximum possible sunshine duration	> 20
Precipitation duration in 0.1 hour	> 20
Precipitation amount in 0.1 mm	> 20
Cloud cover in octants	> 3
Daily mean relative atmospheric humidity in percents	> 10

Table 8: AEX composition and index weighting (July 2008)

Company	Sector	Index weighting (%)
Aegon	life insurance	3.77
Ahold	food retailers and wholesalers	2.70
Akzo Nobel	specialty chemicals	3.34
ArcelorMittal	steel	16.25
ASML	semiconductors	1.83
Corio	real estate holding and development	0.65
DSM	specialty chemicals	1.31
Fortis	banks	6.15
Heineken	brewers	2.23
ING Group	life insurance	12.63
KPN	fixed line telecommunications	5.68
Philips	consumer electronics	6.54
Randstad Holding	business training and employment agencies	0.77
Reed Elsevier	publishing	1.93
Royal Dutch Shell	integrated oil and gas	17.89
SBM Offshore	oil equipment and services	0.86
TNT	delivery services	2.12
TomTom	telecommunications equipment	0.64
Unibail-Rodamco	real estate investment trusts	3.15
Unilever	food products	8.35
Wolters Kluwer	publishing	1.21

Since March 2008 Tele Atlas, Vedior, Hagemeyer, and Corporate Express are removed from the index

Table 9: Augmented Dickey-Fuller test for a unit root

	t-statistic	p-value	SIC lag number**
AEX - Log return	-81,98263	0,0001*	0
Ahold - Log return	-48,96585	0,0001*	0
Heineken - Log return	-59,73040	0,0001*	1
Unilever - Log return	-92,23919	0,0001*	0
Cloud cover - unprocessed	-40,86105	0,0000*	1
Cloud cover - difference in relation to previous day	-37,78033	0,0000*	6
Cloud cover - difference in relation to monthly average	-51,37967	0,0001*	0
Humidity - unprocessed	-17,47332	0,0000*	6
Humidity - difference in relation to previous day	-50,88976	0,0001*	3
Humidity - difference in relation to monthly average	-26,32100	0,0000*	4
Precipitation - unprocessed	-46,75250	0,0001*	1
Precipitation - difference in relation to previous day	-52,24365	0,0001*	3
Precipitation - difference in relation to monthly average	-47,32675	0,0001*	1
Temperature - unprocessed	-8,06698	0,0000*	8
Temperature - difference in relation to previous day	-48,67323	0,0001*	3
Temperature - difference in relation to monthly average	-27,25485	0,0000*	2
Extreme weather day in relation to monthly average	-50,87398	0,0001*	1
Extreme weather day in relation to previous day	-74,58959	0,0001*	0

* unit root rejected at the 1% level

** SIC lag number is based on the number of lagged difference terms in the test equation determined by automatic selection using Schwarz Information Criterion

Table 10: Return correlation matrix

	Unilever	Ahold	Heineken	AEX index
Unilever	1	0,201**	0,285**	0,265**
Ahold		1	0,316**	0,477**
Heineken			1	0,434**
AEX index				1

* small correlation effect

** medium correlation effect

*** large correlation effect

Table 11: Weather correlation matrix – Unprocessed data

	Temperature	Precipitation	Cloud Cover	Humidity
Temperature	1	0,049*	(0,139)*	(0,322)**
Precipitation		1	0,316**	0,251**
Cloud Cover			1	0,570***
Humidity				1

* small correlation effect

** medium correlation effect

*** large correlation effect

Table 12: Weather correlation matrix – Difference from previous day data

	Temperature	Precipitation	Cloud Cover	Humidity
Temperature	1	0,063*	0,118*	(0,108)*
Precipitation		1	0,258**	0,317**
Cloud Cover			1	0,480**
Humidity				1

* small correlation effect

** medium correlation effect

*** large correlation effect

Table 13: Weather correlation matrix – Difference from monthly average data

	Temperature	Precipitation	Cloud Cover	Humidity
Temperature	1	0,033*	0,012*	(0,130)*
Precipitation		1	0,322**	0,259**
Cloud Cover			1	0,554***
Humidity				1

* small correlation effect

** medium correlation effect

*** large correlation effect

Table 14: Single regressions for AEX returns – Unprocessed data (January 3rd 1983 – May 30th 2008)

Weather variable	R	R^2	Coefficient	F	t	sig.
Temperature	0,230	0,001	(0,00000210)	3,620	(1,903)	0,057***
Cloud cover	0,200	0,000	(0,00005100)	2,598	(1,612)	0,107
Humidity	0,002	0,000	(0,00000098)	0,019	(0,138)	0,890
Precipitation	0,003	0,000	(0,00000035)	0,057	(0,240)	0,811

* significant at 1% level
** significant at 5% level
*** significant at 10% level

Table 15: Regression model for AEX returns – Unprocessed data (January 3rd 1983 – May 30th 2008)

Model	Included variables	R	R^2	F	sign.	Coefficient	t	sign.	Durbin-Watson statistic
1	Temperature	0,023	0,001	3,620	0,057***	(0,00000210)	(1,903)	0,057***	2,014
2	Temperature	0,033	0,001	3,606	0,027**	(0,00000240)	(2,148)	0,032**	
	Cloud cover					(0,00006100)	(1,895)	0,058***	
3	Temperature	0,034	0,001	2,486	0,059***	(0,00000250)	(2,186)	0,029**	
	Cloud cover					(0,00006600)	(1,953)	0,051***	
	Precipitation					(0,00000076)	0,497	0,619	

* significant at 1% level
** significant at 5% level
*** significant at 10% level

Table 16: Regression model for Ahold returns – Unprocessed data (January 3rd 1983 – May 30th 2008)

Model	Included variables	R	R^2	F	sign.	Coefficient	t	sign.	Durbin-Watson statistic
1	Precipitation	0,006	0,000	0,269	0,604	(0,00000140)	(0,519)	0,604	1,951
2	Precipitation	0,010	0,000	0,337	0,714	(0,00000190)	(0,662)	0,508	
	Humidity					0,00000885	0,635	0,525	
3	Precipitation	0,010	0,000	0,225	0,879	(0,00000190)	(0,661)	0,509	
	Humidity					0,00000907	0,611	0,541	
	Temperature					0,00000010	0,043	0,966	

* significant at 1% level
** significant at 5% level
*** significant at 10% level

Table 17: Regression model for Heineken returns – Unprocessed data
(January 3rd 1983 – May 30th 2008)

Model	Included variables	R	R^2	F	sign.	Coefficient	t	sign.	Durbin-Watson statistic
1	Humidity	0,021	0,000	2,995	0,084***	(0,00001500)	(1,731)	0,84***	1,965
2	Humidity	0,025	0,001	2,042	0,130	(0,00001300)	(1,413)	0,158	
	Precipitation					(0,00000190)	(1,043)	0,297	
3	Humidity	0,026	0,001	1,537	0,203	(0,00001500)	(1,577)	0,115	
	Precipitation					(0,00000170)	(0,930)	0,353	
	Temperature					(0,00000110)	(0,727)	0,467	

* significant at 1% level
** significant at 5% level
*** significant at 10% level

Table 18: Regression model for Unilever returns – Unprocessed data
(January 3rd 1983 – May 30th 2008)

Model	Included variables	R	R^2	F	sign.	Coefficient	t	sign.	Durbin-Watson statistic
1	Temperature	0,022	0,000	3,250	0,071***	(0,00000270)	(1,803)	0,071***	2,249
2	Temperature	0,025	0,001	2,036	0,131	(0,00000220)	(1,416)	0,157	
	Humidity					0,00000898	0,907	0,365	
3	Temperature	0,027	0,001	1,596	0,188	(0,00000200)	(1,282)	0,200	
	Humidity					0,00001150	1,109	0,268	
	Precipitation					(0,00000170)	(0,846)	0,397	

* significant at 1% level
** significant at 5% level
*** significant at 10% level

Table 19: Regression model for AEX returns – Difference from previous day data
(January 3rd 1983 – May 30th 2008)

Model	Included variables	R	R^2	F	sign.	Coefficient	t	sign.	Durbin-Watson statistic
1	Temperature	0,021	0,000	2,978	0,084***	0,00000606	1,726	0,084***	2,012
2	Temperature	0,026	0,001	2,258	0,105	0,00000658	1,860	0,063***	
	Cloud cover					(0,00004000)	(1,240)	0,215	
3	Temperature	0,027	0,001	1,671	0,171	0,00000649	1,835	0,066***	
	Cloud cover					(0,00004600)	(1,378)	0,168	
	Precipitation					0,00000087	0,705	0,481	
4	Temperature	0,028	0,001	1,320	0,260	0,00000687	1,902	0,057***	
	Cloud cover					(0,00005500)	(1,463)	0,144	
	Precipitation					0,00000071	0,561	0,575	
	Humidity					0,00000537	0,518	0,604	

* significant at 1% level
** significant at 5% level
*** significant at 10% level

Table 20: Regression model for Ahold returns – Difference from previous day data (January 3rd 1983 – May 30th 2008)

Model	Included variables	R	R^2	F	sign.	Coefficient	t	sign.	Durbin-Watson statistic
1	Temperature	0,013	0,000	1,185	0,276	(0,00000730)	(1,089)	0,276	1,950
2	Temperature	0,014	0,000	0,633	0,531	(0,00000710)	(1,069)	0,285	
	Precipitation					(0,00000064)	(0,284)	0,776	
3	Temperature	0,014	0,000	0,436	0,727	(0,00000700)	(1,031)	0,303	
	Precipitation					(0,00000080)	(0,335)	0,737	
	Humidity					0,00000358	0,204	0,838	
4	Temperature	0,014	0,000	0,328	0,859	(0,00000690)	(1,000)	0,317	
	Precipitation					(0,00000078)	(0,325)	0,745	
	Humidity					0,00000423	0,215	0,830	
	Cloud cover					(0,00000520)	(0,073)	0,942	

* significant at 1% level
** significant at 5% level
*** significant at 10% level

Table 21: Regression model for Heineken returns – Difference from previous day data (January 3rd 1983 – May 30th 2008)

Model	Included variables	R	R^2	F	sign.	Coefficient	t	sign.	Durbin-Watson statistic
1	Humidity	0,011	0,000	0,795	0,373	(0,00000950)	(0,892)	0,373	1,962
2	Humidity	0,015	0,000	0,711	0,491	(0,00000860)	(0,801)	0,423	
	Temperature					0,00000345	0,791	0,429	
3	Humidity	0,017	0,000	0,626	0,598	(0,00000440)	(0,356)	0,722	
	Temperature					0,00000403	0,908	0,364	
	Cloud cover					(0,00003100)	(0,676)	0,499	
4	Humidity	0,018	0,000	0,548	0,700	(0,00000610)	(0,480)	0,631	
	Temperature					0,00000383	0,860	0,390	
	Cloud cover					(0,00003400)	(0,733)	0,463	
	Precipitation					0,00000087	0,561	0,575	

* significant at 1% level
** significant at 5% level
*** significant at 10% level

Table 22: Regression model for Unilever returns - Difference from previous day data (January 3rd 1983 – May 30th 2008)

Model	Included variables	R	R^2	F	sign.	Coefficient	t	sign.	Durbin-Watson statistic
1	Precipitation	0,016	0,000	1,749	0,186	(0,00000210)	(1,323)	0,186	2,249
2	Precipitation	0,020	0,000	1,348	0,260	(0,00000200)	(1,259)	0,208	
	Temperature					(0,00000450)	(0,973)	0,331	
3	Precipitation	0,020	0,000	0,900	0,440	(0,00000200)	(1,209)	0,227	
	Temperature					(0,00000450)	(0,956)	0,339	
	Humidity					0,00000071	0,059	0,953	
4	Precipitation	0,021	0,000	0,737	0,567	(0,00000210)	(1,256)	0,209	
	Temperature					(0,00000490)	(1,032)	0,302	
	Humidity					(0,00000240)	(0,175)	0,861	
	Cloud cover					0,00002480	0,499	0,618	

* significant at 1% level
** significant at 5% level
*** significant at 10% level

Table 23: Regression model for AEX returns – Difference from monthly average data (January 3rd 1983 – May 30th 2008)

Model	Included variables	R	R^2	F	sign.	Coefficient	t	sign.	Durbin-Watson statistic
1	Cloud cover	0,025	0,001	4,273	0,039**	(0,00006700)	(2,067)	0,039**	2,013
2	Cloud cover	0,026	0,001	2,326	0,098***	(0,00007400)	(2,155)	0,031**	
	Precipitation					0,00000094	0,616	0,538	
3	Cloud cover	0,026	0,001	1,551	0,199	(0,00007400)	(2,155)	0,031**	
	Precipitation					0,00000095	0,617	0,537	
	Temperature					(0,00000006)	(0,031)	0,975	

* significant at 1% level
** significant at 5% level
*** significant at 10% level

Table 24: Regression model for Ahold returns – Difference from monthly average data (January 3rd 1983 – May 30th 2008)

Model	Included variables	R	R^2	F	sign.	Coefficient	t	sign.	Durbin-Watson statistic
1	Precipitation	0,007	0,000	0,300	0,584	(0,00000150)	(0,548)	0,584	1,951
2	Precipitation	0,010	0,000	0,360	0,698	(0,00000200)	(0,697)	0,486	
	Humidity					0,00001010	0,649	0,517	
3	Precipitation	0,011	0,000	0,252	0,860	(0,00000200)	(0,682)	0,495	
	Humidity					0,00000971	0,615	0,539	
	Temperature					(0,00000074)	(0,189)	0,850	

* significant at 1% level
** significant at 5% level
*** significant at 10% level

Table 25: Regression model for Heineken returns – Difference from monthly average data (January 3rd 1983 – May 30th 2008)

Model	Included variables	R	R^2	F	sign.	Coefficient	t	sign.	Durbin-Watson statistic
1	Humidity	0,027	0,001	4,833	0,028**	(0,00002200)	(2,198)	0,028**	1,965
2	Humidity	0,029	0,001	2,798	0,061***	(0,00001900)	(1,897)	0,058***	
	Precipitation					(0,00000160)	(0,874)	0,382	
3	Humidity	0,029	0,001	1,922	0,124	(0,00001900)	(1,181)	0,069***	
	Precipitation					(0,00000170)	(0,901)	0,368	
	Temperature					0,00000105	0,412	0,680	

* significant at 1% level
** significant at 5% level
*** significant at 10% level

Table 26: Regression model for Unilever returns – Difference from monthly average data (January 3rd 1983 – May 30th 2008)

Model	Included variables	R	R^2	F	sign.	Coefficient	t	sign.	Durbin-Watson statistic
1	Temperature	0,025	0,001	4,184	0,041**	(0,00000550)	(2,045)	0,041**	2,249
2	Temperature	0,026	0,001	2,273	0,103	(0,00000530)	(1,949)	0,051***	
	Humidity					0,00000638	0,602	0,547	
3	Temperature	0,028	0,001	1,772	0,150	(0,00000510)	(1,884)	0,060***	
	Humidity					0,00000894	0,814	0,416	
	Precipitation					(0,00000170)	(0,877)	0,381	

* significant at 1% level
** significant at 5% level
*** significant at 10% level

Table 27: Regression model for AEX returns – Extreme weather days (January 3rd 1983 – May 30th 2008)

Model	Included variables	R	R^2	F	sign.	Coefficient	t	sign.	Durbin-Watson statistic
1	Previous day	0,019	0,000	2,388	0,122	0,00000000	(1,545)	0,122	2,013
2	Monthly average	0,003	0,000	0,073	0,787	(0,00003800)	(0,270)	0,787	2,013

* significant at 1% level
** significant at 5% level
*** significant at 10% level

Table 28: Regression model for Ahold returns – Extreme weather days
(January 3rd 1983 – May 30th 2008)

Model	Included variables	R	R^2	F	sign.	Coefficient	t	sign.	Durbin-Watson statistic
1	Previous day	0,004	0,000	0,101	0,751	0,00009710	0,317	0,751	1,950
2	Monthly average	0,012	0,000	1,032	0,310	0,00000000	(1,016)	0,310	1,951

* significant at 1% level
** significant at 5% level
*** significant at 10% level

Table 29: Regression model for Heineken returns – Extreme weather days
(January 3rd 1983 – May 30th 2008)

Model	Included variables	R	R^2	F	sign.	Coefficient	t	sign.	Durbin-Watson statistic
1	Previous day	0,009	0,000	0,485	0,486	0,00000000	(0,697)	0,486	1,963
2	Monthly average	0,009	0,000	0,590	0,442	0,00000000	0,768	0,442	1,963

* significant at 1% level
** significant at 5% level
*** significant at 10% level

Table 30: Regression model for Unilever returns – Extreme weather days
(January 3rd 1983 – May 30th 2008)

Model	Included variables	R	R^2	F	sign.	Coefficient	t	sign.	Durbin-Watson statistic
1	Previous day	0,009	0,000	0,491	0,483	0,00000000	0,701	0,483	2,249
2	Monthly average	0,011	0,000	0,750	0,387	0,00000000	0,866	0,387	2,248

* significant at 1% level
** significant at 5% level
*** significant at 10% level

Appendix

Figure 17: Map of weather stations in the Netherlands

Table 31: Inhabitants per province

	Inhabitants	Percentage of total
Zuid- Holland	3.455.097	21,20%
Noord- Holland	2.613.070	15,90%
Noord- Brabant	2.419.042	14,80%
Gelderland	1.979.059	12,10%
Utrecht	1.190.604	7,10%
Limburg	1.127.805	7,00%
Overijssel	1.116.374	6,80%
Friesland	642.209	3,90%
Groningen	573.614	3,50%
Drenthe	486.197	2,90%
Zeeland	380.497	2,30%
Flevoland	374.424	2,20%
Total	**16.357.992**	**100,0%**

Table 32: Single regressions for Ahold returns – Unprocessed data (January 3rd 1983 – May 30th 2008)

Weather variable	R	R^2	Coefficient	F	t	sig.
Temperature	0,003	0,000	(0,00000043)	0,042	(0,204)	0,838
Cloud cover	0,006	0,000	0,00002270	0,212	0,461	0,645
Humidity	0,006	0,000	0,00000650	0,235	0,485	0,628
Precipitation	0,006	0,000	(0,00000140)	0,269	(0,519)	0,604

* significant at 1% level
** significant at 5% level
*** significant at 10% level

Table 33: Single regressions for Heineken returns – Unprocessed data (January 3rd 1983 – May 30th 2008)

Weather variable	R	R^2	Coefficient	F	t	sig.
Temperature	0,003	0,000	(0,00000036)	0,070	(0,264)	0,792
Cloud cover	0,016	0,000	(0,00005100)	1,741	(1,3192)	0,187
Humidity	0,021	0,000	(0,00001500)	2,995	(1,731)	0,084***
Precipitation	0,018	0,000	(0,00000260)	2,085	(1,444)	0,149

* significant at 1% level
** significant at 5% level
*** significant at 10% level

Table 34: Single regressions for Unilever returns – Unprocessed data
(January 3rd 1983 – May 30th 2008)

Weather variable	R	R^2	Coefficient	F	t	sig.
Temperature	0,022	0,000	(0,00000270)	3,250	(1,803)	0,071***
Cloud cover	0,004	0,000	(0,00001400)	0,117	(0,341)	0,733
Humidity	0,018	0,000	(0,00001350)	2,068	(1,438)	0,150
Precipitation	0,008	0,000	(0,00000120)	0,414	(0,643)	0,520

* significant at 1% level
** significant at 5% level
*** significant at 10% level

Table 35: Single regressions for AEX returns – Difference from previous day data
(January 3rd 1983 – May 30th 2008)

Weather variable	R	R^2	Coefficient	F	t	sig.
Temperature	0,021	0,000	0,00000606	2,978	1,726	0,084***
Cloud cover	0,013	0,000	(0,00003300)	1,056	(1,028)	0,304
Humidity	0,003	0,000	(0,00000190)	0,050	(0,224)	0,823
Precipitation	0,006	0,000	(0,00000056)	0,227	0,476	0,634

* significant at 1% level
** significant at 5% level
*** significant at 10% level

Table 36: Single regressions for Ahold returns – Difference from previous day data
(January 3rd 1983 – May 30th 2008)

Weather variable	R	R^2	Coefficient	F	t	sig.
Temperature	0,013	0,000	(0,00000730)	1,185	(1,089)	0,276
Cloud cover	0,002	0,000	(0,00001100)	0,030	(0,173)	0,863
Humidity	0,003	0,000	0,00000357	0,047	0,217	0,828
Precipitation	0,004	0,000	(0,00000079)	0,124	(0,352)	0,725

* significant at 1% level
** significant at 5% level
*** significant at 10% level

Table 37: Single regressions for Heineken returns – Difference from previous day data (January 3rd 1983 – May 30th 2008)

Weather variable	R	R^2	Coefficient	F	t	sig.
Temperature	0,011	0,000	(0,00000382)	0,780	0,883	0,377
Cloud cover	0,011	0,000	(0,00003500)	0,765	(0,874)	0,382
Humidity	0,011	0,000	(0,00000950)	0,795	(0,892)	0,373
Precipitation	0,003	0,000	0,00000037	0,063	0,250	0,802

* significant at 1% level

** significant at 5% level

*** significant at 10% level

Table 38: Single regressions for Unilever returns – Difference from previous day data (January 3rd 1983 – May 30th 2008)

Weather variable	R	R^2	Coefficient	F	t	sig.
Temperature	0,013	0,000	(0,00000490)	1,111	(1,054)	0,292
Cloud cover	0,000	0,000	0,00000051	0,000	0,012	0,990
Humidity	0,003	0,000	(0,00000270)	0,057	(0,240)	0,811
Precipitation	0,016	0,000	(0,00000210)	1,749	(1,323)	0,186

* significant at 1% level

** significant at 5% level

*** significant at 10% level

Table 39: Single regressions for AEX returns – Difference from monthly average data (January 3rd 1983 – May 30th 2008)

Weather variable	R	R^2	Coefficient	F	t	sig.
Temperature	0,000	0,000	(0,00000008)	0,001	(0,037)	0,970
Cloud cover	0,025	0,001	(0,00006700)	4,273	(2,067)	0,039**
Humidity	0,008	0,000	(0,00000520)	0,435	(0,660)	0,509
Precipitation	0,001	0,000	(0,00000001)	0,007	(0,081)	0,935

* significant at 1% level

** significant at 5% level

*** significant at 10% level

Table 40: Single regressions for Ahold returns – Difference from monthly average data (January 3rd 1983 – May 30th 2008)

Weather variable	R	R^2	Coefficient	F	t	sig.
Temperature	0,004	0,000	(0,00000120)	0,089	(0,298)	0,766
Cloud cover	0,003	0,000	0,00001740	0,081	0,284	0,776
Humidity	0,006	0,000	(0,00000732)	0,235	0,485	0,628
Precipitation	0,007	0,000	(0,00000150)	0,300	(0,548)	0,584

* significant at 1% level

** significant at 5% level

*** significant at 10% level

Table 41: Single regressions for Heineken returns – Difference from monthly average (January 3rd 1983 – May 30th 2008)

Weather variable	R	R^2	Coefficient	F	t	sig.
Temperature	0,008	0,000	0,00000159	0,402	0,634	0,526
Cloud cover	0,019	0,000	(0,00006100)	2,349	(1,533)	0,125
Humidity	0,027	0,001	(0,00002200)	4,833	(2,198)	0,028**
Precipitation	0,017	0,000	(0,00000250)	1,998	(1,413)	0,158

* significant at 1% level

** significant at 5% level

*** significant at 10% level

Table 42: Single regressions for Unilever returns – Difference from monthly average (January 3rd 1983 – May 30th 2008)

Weather variable	R	R^2	Coefficient	F	t	sig.
Temperature	0,025	0,001	(0,00000550)	4,184	(2,045)	0,041**
Cloud cover	0,008	0,000	(0,00002900)	0,464	(0,681)	0,496
Humidity	0,011	0,000	0,00000907	0,746	0,864	0,388
Precipitation	0,009	0,000	(0,00000140)	0,546	(0,751)	0,453

* significant at 1% level

** significant at 5% level

*** significant at 10% level