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Major Financial Economics

Stock market anomalies: is the weather effect present in the Amsterdam Stock Exchange?

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PREFACE AND ACKNOWLEDGEMENTS

This thesis is the final work of my degree, International Bachelor Economics and Business Economics. The idea for this research stemmed from my appreciation of good weather. Combined with the stock market this led to investigating the existence of the weather effect. Mainly, because I personally think it is fascinating how people are influenced by external incentives like the weather.

I could not have achieved this thesis without Erasmus School of Economics and the professors who taught me the skills needed to write this thesis. I would like to thank everyone with the guidance and support during my bachelor and this thesis.

ABSTRACT

In this thesis the existence of the weather effect in the Amsterdam Exchange (AEX) is investigated during a 14 year time period from 2005 to 2018. The weather variables used were average temperature, hours of sunshine, duration of rainfall, average windspeed and relative humidity. The AEX stock variables used were stock return and trading volume. Significant influence has been found for stock returns on average temperature and trading volume on average windspeed. Several significant relationships on stock variables have been found for interaction variables. However, a clear weather effect for the AEX stock index cannot be concluded.

Keywords: Stock Returns, Trading Volume, Stock Market, Efficient Market Hypothesis

JEL Classification: G12

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CHAPTER 1 Introduction

In the capital markets a lot of existing factors cause stock market anomalies. Some examples, which have been researched by many economists, are the January effect, day-of-the-week effect, turn-of-the-month effect, holiday effect, time-of-the-day effect, December effect and last the sell in May and go away effect (Joe Marwood, 2018). The effects may be related to the date or day. However, other anomalies are more related to the specific stock or stock performance like the momentum effect, size effect, P/E ratio effect, PEAD effect, IPO effect, stock splits effect, and the book-to-market effect which is also known as the value effect. Many effects have been found in the stock market, only not all of them are. A cause for some of these effects not being as recognized as other effects might be due to the fact that researcher did use data mining when providing the evidence for a new effect. Therefore, Harvey et al. (2015) are doubting the statistical significance of these anomalies. Over time researchers discovered more existing anomalies, while using the same data set. However, it could be possible that not all anomalies have been discovered yet, or are more specific to certain areas than others. In 1980 the Journal of Financial Economics published the first article on the existence of the weather effect in the stock market.

Thus, an extra anomaly might be caused by the weather. It is said that weather does affect mood, and mood again affects investor behaviour. People might experience feelings and react differently as a result of good or bad weather. The change of their actions will have effect on the investments done in the market, therefore changes in equity prices can be due to the weather.

1.1 Existing literature

It has been proven by Mehra and Sah (2002) that mood fluctuations of investors are able to increase the volatility of equity prices. In their research especially discount factors and risk attitudes, have effect on the equilibrium equity prices. According to Saunders (1993) and Trombley (1997) the effect was even more clear at the moment the weather fluctuations were bigger, for example high temperature versus a low temperature one day apart. He also found that cloud cover, the opposite variable to hours of sunshine, had a significant effect on the New York stock prices.

During a decision, feelings can have an effect, thus a change of feelings of the investor can lead to other decisions being made. The idea that investment decisions are influenced by unrelated factors, for example an environmental factor such as the weather, is known as mood misattribution (Lucey and Dowling, 2005). Therefore the weather might be affecting the stock prices indirectly due to the effect weather has on people's behaviour.

In a research conducted by Saunders (1993) it was concluded that the Wall Street weather had a significant effect on the NYSE/AMEX stock prices. For the Shenzhen stock exchange the weather effect appeared to have a significant effect when only looking at the extreme values of temperature, humidity, cloud and sunshine duration (Kang, Jiang and Yoon, 2009). Another important weather factor according to Chang et al. (2008) in intraday stock trading activities appeared to be cloud cover. Cloud cover did affect the stock prices negatively, especially at the beginning of the trading day. Which is in line with the other researches that concluded that sunshine duration had a positive effect, as these are contradictory weather measures. On the other hand, Worthington (2006) concluded from his research on the Australian stock prices there was no significant relationship to be found between the weather and stock returns. Likewise, in China even when looking at the extreme values of weather conditions, there was no result of finding a weather effect on the stock exchange. And even though Chang et al. (2008) found proof for the negative effect of cloud cover on stock returns, a meta-analysis conducted by Keef and Roush (2007) showed that cloud cover only had a significant negative effect when the location was not near the equator, otherwise the relationship did not hold.

As for some stock exchanges having different conclusions than others regarding the weather effect, or two separate studies on the same exchange finding contradictory results, this leads to some questions about the existence of the effect. It could be argued that finding a relationship between the local atmospheric conditions and prices of shares is a result of data mining. Only when using a long time series of data, for example since the beginning of the stock exchange, data mining can be safely excluded. Or another reason for some researchers finding relationships while others do not find a significant effect due to another data period on a given set of stocks. Over time the effect is recognized by traders and they will base their decisions on their knowledge resulting in a less extreme reaction to weather conditions. Another argument for different research outcomes on the existence of the weather effect might be that all stock market exchanges react in another way to the weather. Depending on the market and the sensitivity of investors to the weather might influence the strength of the weather effect.

1.2 Research

The weather effect has proved to affect stock prices in some stock exchange areas, but a conclusion for Amsterdam has not yet been found. This thesis will look at the weather effect more deeply and whether it applies to the Amsterdam Stock Exchange. This leads to the central research question of the thesis:

Does the weather effect exist in the Amsterdam Stock Exchange?

To answer the central research question the research will be divided into two parts. For the first part the hypothesis is stated as follows:

1. ***The weather has effect on investor behaviour.***

The first hypothesis is to be solved based on theory. It is important to look at whether the atmospheric conditions influence the mood and behaviour of people, thus investors will be influenced as well. Because the idea of the weather effect is that people change their investment decisions due to the changing weather conditions. Thus, only if it is proven that the weather indeed causes the investors to behave differently it could be argued that there is a possible weather effect. The first hypothesis will be answered by using the two smaller hypotheses which are stated as:

1.1 Weather conditions do affect mood.

1.2 Emotions do affect decision making.

Based on these two smaller statements, it can be concluded whether the climate will have effect on investor behaviour.

The second part of the research is important when the first hypothesis holds, because only if the weather-induced mood affects the investment decisions made by people possible further relationships between the weather and stock returns and trading volume are relevant. The second part of the thesis will be solved by using data of weather conditions and stock data. It will look at whether the weather does affect the AEX. Stock returns and trading volumes will be used to determine the influence of climate circumstances. Thus the second part will be made up by hypothesis two, which is focused on stock returns, and hypothesis number three, which is aimed at trading volumes. For both of these hypotheses there will be smaller statements which combines the weather variables to the stock data. As five weather factors will be used, namely hours of sunshine, average temperature, duration of rainfall, average windspeed and relative humidity, both of the hypotheses will follow the same construction. They both consist of five smaller statements to answer the hypotheses

The second hypothesis, which is focussed at stock returns, is stated as follows:

2. ***Weather does affect stock returns.***

As already mentioned this statement will be answered by making use of smaller hypotheses related to five chosen weather variables. The factors used to look at should not be too complicated as they should be notable for the investors. This means looking at air pressure or global radiation is not as important as other variables as most people are less aware of these values compared to other variables. It is more important to make use of simpler weather factors of which investors are conscious, therefore more standard weather factors are used to look at the change in stock prices.

The first factor is the amount of sunshine as a percentage of the longest possible hours of sun for that specific day. Taking this as a percentage is more accurate as during the year the maximum hours of sunshine a day vary, especially when comparing the longest and shortest day in the year. Therefore looking at the percentage is necessarily to look at the effect on the returns. By doing this the seasonality of the variables is removed, which is essential in an analysing the data. The factor hours of sunshine leads to the second hypothesis, stated as:

2.1. Hours of sunshine is positively correlated to stock returns.

The second factor important for answering the sub-question is the average temperature during the day. But the average temperature might be high for one moment of the year, but low for another time of the year. Therefore, this average temperature will be compared to the average normal temperature for that given month. This way it can be seen whether the average temperature is considered high, low or normal for that moment. This is also done to remove seasonality. Based on the average temperature compared to the normal temperature during the time of the year. However, Cao and Wei (2005) did find in their extension on previous research that the temperature did have a negative effect. But this research was followed up by Kaustia and Rantapuska (2016) who showed that temperature had a positive effect on stock returns. The third hypothesis is as follows:

2.2. The average temperature of the day has a positive correlation with stock returns.

The next factor that will be used for looking at the effect of weather on the prices of equity is the duration of rainfall during the day. The rainfall is measured in its length of time as a full day of rain has a more negative impact than a short heavy rainfall. As the duration of rainfall during the day increases, this will probably be perceived by investors as bad weather. Thus, this would mean that if the hours of rainfall increases it influences the stock prices negatively. The hypothesis to look at the effect of the duration of rainfall is:

2.3. The duration of rainfall during the day is negatively correlated with stock returns.

The fourth factor that will be used for looking at the influence of weather on stock prices is windspeed. This weather variable is used because some researches did find that it would lead to colder weather and would have a negative effect on the stock prices. Thus the fourth hypothesis is:

2.4. The stock returns are negatively affected by the local windspeed.

As mentioned earlier Yoon and Kang (2009) found that humidity had a negative relationship with stock prices in Korea, however after the crisis this relationship was not significant anymore. However, as some other researches did indeed find that humidity has a negative effect on stock prices the last hypothesis looking at stock prices is states as:

2.5. Relative humidity does negatively affect the stock returns.

The five hypotheses 2.1 until 2.5 will be used to look at the weather effect on the equity prices of the AEX. However, this is not the only stock data variable used to look at the stock market anomaly, therefore trading volume of the AEX is used as well. This will be the third hypothesis and will be answered by using the same build-up as hypothesis 2, thus by use of five smaller statements. The last hypothesis is stated as:

3. The weather does influence trading volume.

The weather effect does not only have to influence the stock prices, as due to weather circumstances people their emotions change. These emotions can be the cause for different types of behaviour. And if for example an investor is happy and will be more optimistic, it can lead to bigger investments, thus higher trading volumes. Every type of emotion, caused by the weather, can create its own investment strategies and affect the volume that is traded in the market.

The first factor that will be considered as an influence on trading volume is hours of sunshine as a percentage of the maximum hours of sunshine. Again this is done, like in statement 2.1, to remove the seasonality of the variable. According to research conducted by Huang and Goo (2008) trading volume was an important indicator of trading behaviour. And it appeared that a good mood did lead to overconfidence in trading strategies which did increase the volume that was traded. Therefore the first statement is as follows:

3.1. *Hours of sunshine has a positive effect on the volume that is traded.*

The second weather factor is the average temperature during the day. Fleming et al (2006) found that temperature was an important weather condition. The state of the climate could influence the volatility of the market. Trading volume would as well me more volatile, which could lead in extreme cases to trading volume. This would be logical because higher or lower than normal temperatures could lead to other than normal behaviour as well. As a result trading volume will be affected by the changing behaviour leading to the following statement:

3.2. *The average temperature fluctuations will lead to trading volume differences.*

The next variable is the duration of rainfall. This will most likely negatively influence behaviour as most people do not prefer rainfall. Therefore investors are assumed to be less optimistic, which can be reflected in their trading behaviour as well. Therefore the third statement for answering the third hypothesis is:

3.3. *The duration of rainfall will be negatively correlated to the trading volume.*

For the fourth variable windspeed only limited information can be found. No significant evidence of relationships between windspeed and investment behaviour was found. However, it seems logical that most people prefer a normal wind speed and no extreme values because those would indicate storms. A high windspeed probably will affect behaviour negatively, thus investors will be less optimistic which reduces the trading volume. Therefore the corresponding hypothesis will be:

3.4. Windspeed does have a negative effect on trading volume.

The last factor that will be used to look at trading volume is relative humidity. Howarth and Hoffman (1984) found in their research that humidity had a negative correlation with positive human performance. Thus an increase of relative humidity would lead to more negative behaviour by humans, which later has been proven in the Spanish stock market by Pardo and Valor (2003). The last hypothesis for statement three will be:

3.5. Relative humidity is negatively correlated with trading volume.

All of these smaller hypotheses will be used to answer the three main hypotheses. Together these will be combined to form a conclusion on the central research question. A clear overview of the research can be found in Table 1.1.

1.3 Relevance

Looking at whether there is a possible weather effect existent in the Amsterdam Stock Exchange is relevant for the economy as it explains more about the movement of stock prices. If the prices of equity would suddenly increase, and none of the other anomalies would be able to explain this, the weather effect might bring a new solution to the unexpected change in prices. Good weather will affect stock prices positively, and bad weather conditions will affect the prices negatively, according to expectations.

Additionally, if the existence of the weather effect is recognized, investors might change their behaviour. When anomalies are discovered, investors will exploit the benefits by changing their trading behaviour to a more profitable strategy. McLean and Pontiff (2015) found confirmation for the disappearing anomalies as a result of academic publications. As anomalies are published, investors will trade based on this extra knowledge. The recognition of anomalies will diminish the effect of the anomaly. Depending on the efficiency of the market the weather effect disappears as traders start to take the extra information into account. The idea of incorporating the weather conditions in the trading prices is in line with the efficient market hypothesis (EMH). If the prices would truly reflect all available information it should not be possible to find a weather effect as the weather is observable by everyone and can be used in the investors' trading strategy. Especially, when the weather is perfectly predictable, it should already be incorporated into the stock prices. The existence of the weather effect in a market questions the efficient market hypothesis.

In case the weather effect would be existent, the computer models for investments should incorporate the weather predictions as well. While the stock pricing these days is much done with use of artificial intelligence computer programs which make sure predictions of returns are done without behavioural biases (Borzykowski, 2017). This would lead to more accurate predictions of the stock prices than previously would have been possible. But, as a result of possibly incorporating this into the investment algorithms, the weather effect will be less clear or even non-existent as this effect is caused by human behaviour due to emotional trading. Which means that the more developed way of investing these days could lead to fewer market anomalies.

More importantly, if the weather effect would be a recognized market anomaly this can be exploited by investors. If the weather causes predictable patterns in stock returns investors are able to trade based on their knowledge. If this information is used in a strategic way, it should be possible to outperform the market using their investor strategies (Malkiel, 2004).

1.4 Main findings

The main findings of previous conducted research differ in their conclusions. In most researches the effect of weather variables on the stock returns were investigated. However, the results of these papers have contradictory outcomes which might be caused by the different stock markets which they were focussed on. The weather variables of which most results were found are temperature, hours of sunshine, cloudiness and humidity. It differs per stock market which of the variables were considered significant and which were not.

1.5 Overview

The thesis is structured as follows; in the Literature Review the first hypothesis will be answered by use of previous researches done on the effect of weather on changes in human behaviour. After this the stock return and weather data is introduced, transformed and used for the analysis of the thesis. The results of the analysis on the weather effect in the Amsterdam Stock Exchange will be used to answer the second and third hypothesis. And to end the thesis in the conclusion the research question will be answered and is followed by a discussion and recommendations for further research.

CHAPTER 2 Literature Review

To answer the first hypothesis a deeper look into previous research is done by looking at what conclusions have been drawn about the effect of weather on human behaviour. This can be put into a model which consist of three factors, namely weather variables, mood and behaviour according to Howarth and Hoffman (1984). The idea behind the model is that individuals perceive the weather variables, which will have an effect on their mood or emotional state. This state of mind will lead to individuals choosing to engage in particular behaviour. Thus, first is important that the weather will affect the mood, and the mood again will have effect on the decision being made.

2.1 Weather conditions affecting mood

Studies so far have led to diverse conclusions about the effect of weather on the mood of people. The different results and consequences of those findings for this thesis will be made clear in this section.

Most studies did indeed find that weather has an effect on the mood of individuals, but most of the conclusions are drawn under certain conditions. To start, Keller et al. (2005) focussed on the mood changes of individuals when considering as well the amount of time spent outside and the season of the year. People who did spent more time outside would react more heavily to the weather conditions than others spending less time in the open air. Thus, spending time outside makes the participants more responsive to the weather conditions, mainly temperature was an important factor. The season was of importance for the outcome of the research as well. Here it appeared that temperature was an essential weather variable, a higher temperature in spring led to an increase in mood. However, in summer a higher temperature would have an opposite effect as the extremely high temperatures are experienced by individuals as unpleasant.

Which is in line with Denissen et al. (2008) who found that the weather variable hours of sunshine was a variable important to take in consideration and was differing per season. Because the variable can have fluctuations within one season, as the summer consists of sunny and cloudy days. Between seasons large fluctuations can appear as during summer the maximum amount of sunshine hours is longer than during the winter season. However, they found that sunshine did not have a significant effect on a positive mood, but they found that lack of sunshine caused negative affect and tiredness among the subjects. A lower vitamin D_3 level might be the reason for these mood reactions, because the skin produces this vitamin when it absorbs sunlight. Which is in line with the research conducted by Lansdowne (1998) who found that vitamin D_3 did enhance the mood of participants during winter. Positive affect was enhanced due to vitamin D_3 while negative affect was reduced. But this effect was also different between the subjects as some reacted more heavily, subjects suffering from SAD, a seasonal affective disorder, appeared to be more sensitive to weather changes. People differ in their sensitivity to the daily weather circumstances. Thus, some individuals may be affected by the weather conditions, while others do not seem to change mood or behaviour.

Spasova (2012) looked deeper into the individual characteristics that make individuals react differently to changes in the weather. An important finding of this research was that the emotional state of women was more affected by changes in the weather compared to men. The Chartered Financial Analyst (2016), a global association for investment professionals, took a deeper look into the composition of its membership. The CFA Institute found that only 14.1% of their Dutch CFA members were female. If this would be the case, the effect of weather on the stock prices could be less heavily as men react less heavily to weather changes but invest more compared to women.

According to several researches that have been conducted it is clear that the weather indeed has got some effect on mood. However, the strength of this effect can be dependent on several factors like time spent outside, seasons, personal conditions and gender. Now it is important to look at whether the mood change can result in a different decision being made, which will be done in the next section.

2.2 Emotional state and decision making

In the traditional decision making theory it was assumed that people would base their decisions on maximum utility. This would mean that people make their decisions based on the traditional model where the costs and benefits are weighed against each other to establish possible outcomes and the best one of these is chosen. However, in this risk-benefit trade-off the influence of feelings of the decision-maker is ignored. This is, according to Loewenstein et al. (2001), the consequentialist perspective, because it does not use feelings as an influence on decision making it is a rather unrealistic perspective.

The traditional model was improved by Loomes and Sugden (1982) by involving anticipated emotions in the decision making model. They took into account the emotions which are expected to be felt by the decision maker after a certain decision has been made. The emotions which will be experienced afterwards can be in the case of a negative outcome regret or disappointment. However, as this extended theory does involve decisions experienced after a decision has been made, it does not yet involve the feelings that are experienced at the moment of making the decision.

As a result Schwarz and Clore (1983) took a deeper look into the relationship between mood and decision making. They incorporated the mood of the decision makers in their perspective. It was proven that a good mood at the time of making a decision would lead to a more optimistic decision (Hirschleifer & Shumway, 2003). Also when the mood was more negative, the decision made would be more pessimistic. This was concluded to be true even when the decision in question was not related to the cause of the mood. Thus, incidental affect, which is unrelated to the particular decision, could influence perception of the choice and lead to other decisions being made than would have been made without the affect (Loewenstein and Lerner, 2003).

All of this behaviour can be seen back with investors. Daniel and Titman (1999) and Symronidis et al. (2010) did show this as well in their research that due to overconfidence, which was caused by a good mood, the stock return volatility did increase. The mood of investors can lead to overconfidence, which does not only increase stock price volatility but leads to more aggressive trading behaviour as well (Gervais & Odean, 2001). And as traders behave more aggressively it Gervais and Odean conducted increases in the trading volume. Thus, the emotional state of investors affects their trading behaviour.

First it was thought that decision making was purely based on costs and benefits, but through the years it was found that emotions and feelings did play a role in this. New models were established for the decision making process which did involve the emotions at the time of the decision being made but also the anticipated emotions.

2.3 The effect of weather on decision making

Concluding from the two previous sections, based on previous research, it can be said that the weather influences the mood of people and as a result indirectly the behaviour of people.

Section 2.1 showed that the weather does have effect on the mood of people, thus investors. It became clear that hours of sunshine and temperature affect mood, some researchers suggested that humidity affects the mood of subjects as well. However, the effect of the weather was different between different types of people, thus personal factors are still important for the size of the effect of the weather on mood.

Based on section 2.2 it was proven that different states of emotions could lead to different decisions being made. A positive mood would lead to more optimistic decisions, while a negative mood results in more pessimistic decisions.

To conclude, weather does affect mood which consequently affects the decision making process, as proven in numerous empirical papers. Due to good weather, investors might be more optimistic when investing in equity and the opposite when experiencing bad weather. The goal of this thesis is to look at whether this relationship between the weather and the investing behaviour is visible in the stock prices. Which will be continued in the next chapters.

CHAPTER 3 Data

For looking at the existence of the weather effect in the Amsterdam Stock Exchange a period of 14 years is taken from 01/01/2005 to 31/12/2018. It is the longest possible whole year period as from the 10th of October 2004 the AEX trading volume data was archived in their stock data as well. The daily effect of weather is taken for analysis so there are a total of 3,582 observations. As this research focusses on the effect of weather on the Amsterdam Stock Exchange data on weather conditions and AEX stock prices is necessary.

3.1 Data sources

For the Amsterdam Stock Exchange the AEX stock prices will be used. The AEX index, consisting of the 25 biggest companies in the Netherlands, serves as an indicator for the Dutch stock market. The composition of these 25 stocks is set fixed ever third Friday of March, the value of all stocks together determine the value of the AEX index. Every year has three moments during which adjustments are possible, these events occur on the third Friday of June, September and December. Adjustments are made in case there are more or less than 25 companies in the AEX index as a consequence of mergers, acquisitions, business splits et cetera. Historical data can be retrieved from Yahoo Finance and consists of open and closing price. The highest and lowest stock price that have occurred during the day and the volume of stocks can be retrieved from Yahoo Finance. The currency is presented in EUR currency. Data is available for every day of the year except for the weekends and some specific days during which the Dutch stock market is closed. Thus, every year AEX stock market data is not available on New Years Day, good Friday, Easter Monday, Labour Day and due to Christmas the 25th and 26th of December.

Historical daily data on the weather conditions during the same period as the AEX stock prices is retrieved from the Dutch KNMI website. The measurements from the KNMI location at Schiphol, weather location 240, are used for this thesis. This is their closest measurement location to the Amsterdam Stock Exchange, located 12 kilometres apart. As mentioned in the introduction data is used on the weather factors hours of sunshine, average temperature, duration of rainfall, average windspeed and relative humidity. An overview of the used variables can be found in Table 3.1.

3.2 Descriptive statistics

Section 3.2 will look at all of the variables used for the analysis. First is looked at whether the data is normally or non-normally distributed. This is done by using a Jarque-Bera test, here it can be seen whether the data is normally distributed in terms of skewness and kurtosis. The outcome of this test for all relevant weather factors and stock variables can be found in their own descriptive statistics tables at the bottom. Here both the value of kurtosis and skewness and the corresponding p-values can be found. Almost all variables are non-normally distributed both due to skewness and kurtosis. Except the variables open and closing price are only non-normally distributed due to kurtosis and not because of skewness. That these two variables are non-normally distributed can be seen in their histograms as well, see Histogram 3.1 and Histogram 3.2. Here it is obvious that skewness is not the reason for the non-normal distribution, but kurtosis is.

All of the histograms for the variables volume, sunshine hours in percentages of the total hours of sunshine, average temperature, duration of rainfall, average windspeed and relative humidity, which show the distribution, can be found in Histogram 3.3 till Histogram 3.8.

The histogram for hours of sunshine as a percentage of maximum hours of sunshine (Histogram 3.4) shows an evenly divided amount of observations for every percentage. However, the number of observation for 0 to 3 percent shows an amount of observations around 4 times higher than all other percentages. There is a limited amount of observations for 95 to 100 percent.

Average temperature shows a sort of normal distribution around 100, thus an average temperature of 10 degrees Celsius. However, in the middle there is a slight dip in the histogram and next to it on both the left and right are two peaks around the value of 80 and 150, equal to 8 and 15 degrees Celsius. This can be seen in Histogram 3.5.

The histograms of duration of rainfall and average windspeed (Histogram 3.6 and Histogram 3.7) both show a right-skewed pattern. This is according to expectations as when it rains in the Netherlands, most of the time it does not rain for whole days, thus the most observations are based on the left side of the histogram. As a result the mean is located to the right side of the median which creates a right-skewed graph (Doane & Seward, 2011). The histogram for average windspeed shows its peak around a value of 40, thus 4 meters per second.

The last histogram (Histogram 3.8) is for the relative humidity variable. Most observations are on the right side of the graph, leading to a mean located to the left side of the median. This left-skewed histogram has its highest peak around a value of 84 percent.

Open and closing price

The open and closing price for the AEX can be found on Yahoo finance for every trading day. For the opening and closing price line charts graphs are plotted which can be found in Graph 3.1 and Graph 3.2. It can be seen that the open and closing price display a similar kind of trend. This is because fluctuations during the day will not be big enough to make a large difference between these two lines. Table 3.1 shows that the p-value of kurtosis is lower than the 0.05 significance level however the p-vlaue of skewness is not. These variables are non-normally distributed due to kurtosis, but not due to skewness.

	Open price			**Closing price**		
Mean			411.54			411.43
St. Dev.			86.80			86.80
Min			199.34			199.25
Max			574.92			576.24
Skewness	- 0.0544	*p-value*	0.184	- 0.0551	*p-value*	0.178
Kurtosis	2.078	*p-value*	0.000	2.080	*p-value*	0.000

Table 3.1: Open and closing price

Trading volume

When looking at the trading volume in a line chart graph, to be found in Graph 3.3, it shows a trend which seems to be repeating itself. However, during the period from 2007 to 2009 the trend shows more extreme values for high and low volume moments. The data shows a non-normal distribution which can be seen in Table 3.2 below due to the p-values of kurtosis and skewness.

	Trading volume		
Mean			109,922,009
St. Dev.			42,604,077
Min			0
Max			527,820,900
Skewness	1.973	*p-value*	0.000
Kurtosis	11.692	*p-value*	0.000

Table 3.2: Trading volume

Hours of sunshine

The KNMI data source gives information on the number of hours of sunshine a day. However, during the year the maximum number of hours of sunshine varies due to the seasons. To remove seasonality the number of hours of sunshine is taken as a percentage of the total length of hours of sunshine possible. It is important to look at this weather factor as a percentage as during the shortest day of the year at the sun rises later and goes down earlier. When comparing the longest and shortest day of the year there is a significant difference in the maximum possible hours of sunshine. Thus, in the analysis it is better to use the number of hours of sunshine as a percentage of the longest possible length. The mean and standard deviation per month can be found in Table 3.3. Where it becomes clear that during summer months the average percentage of hours sunshine is higher than during winter. The data is non-normally distributed due to skewness and kurtosis.

	Total	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**June**	**July**	**Aug**	**Sept**	**Oct**	**Nov**	**Dec**
Mean	38.41	25.90	32.22	44.07	49.89	47.68	45.71	46.90	42.75	41.70	36.11	24.76	22.72
St. Dev	29.77	28.23	31.94	31.36	28.09	29.84	28.58	27.45	25.58	28.09	28.65	25.38	26.39
Min	0	0	0	0	0	0	0	0	0	0	0	0	0
Max	94	89	91	94	94	94	93	93	92	92	91	90	87
Skewness	0.268	*p-value*	0.000										
Kurtosis	1.753	*p-value*	0.000										

Table 3.3: Hours of sunshine as a percentage of maximum hours of sunshine

Average temperature

Data on the average temperature is as well retrieved from the KNMI site. The average temperature is given in 0.1 degrees Celsius and is measured during the full 24 hour length of the day. Similar to hours of sunshine as a percentage, the mean value of the average temperature is higher during summer than during winter which can be seen in Table 3.4. Due to kurtosis and skewness the data follows a non-normal distribution.

	Total	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**June**	**July**	**Aug**	**Sept**	**Oct**	**Nov**	**Dec**
Mean	109.35	39.21	36.16	62.07	100.94	137.54	162.88	186.78	176.28	154.49	118.79	77.26	47.64
St. Dev	61.97	40.18	35.07	34.31	30.95	35.24	28.33	29.07	22.35	25.52	28.13	32.43	39.69
Min	-77	-64	-77	-61	31	65	89	135	125	100	31	-16	-74
Max	295	128	113	157	200	234	261	295	262	242	182	156	128
Skewness	-0.196	*p-value*	0.000										
Kurtosis	2.463	*p-value*	0.000										

Table 3.4: Average temperature

Duration of rainfall

The duration of rainfall is a weather variable measured per 0.1 hours. This variable is measured per day as well and represents the time it has been raining during the 24 hour period. Duration of rainfall has a higher mean during winter months compared to summer months. The data follows a non-normal distribution which can be seen in Table 3.5 below.

	Total	Jan	Feb	Mar	Apr	May	June	July	Aug	Sept	Oct	Nov	Dec
Average	16.85	24.30	19.46	14.76	10.04	14.38	11.70	13.46	16.08	14.54	18.18	21.83	23.58
St. Dev	27.29	32.41	29.50	27.68	18.74	26.21	21.28	25.90	25.86	25.81	29.38	28.50	29.28
Min	0	0	0	0	0	0	0	0	0	0	0	0	0
Max	211	156	211	197	119	140	131	187	199	161	169	132	131
Skewness		2.319		*p-value*		0.000							
Kurtosis		9.630		*p-value*		0.000							

Table 3.5: Duration of rainfall

Average windspeed

The average windspeed is measured over a the total 24 hours of the day. The average over this period is taken and given in 0.1 m/s. In Table 3.6 it can be seen that during the winter months the mean average windspeed is higher than during summer. The data follows a non-normal distribution due to kurtosis and skewness.

FG	Total	Jan	Feb	Mar	Apr	May	June	July	Aug	Sept	Oct	Nov	Dec
Average	48.97	59.01	53.55	51.95	47.15	47.35	43.94	44.81	43.28	43.99	47.46	51.27	54.61
St. Dev	21.30	28.69	22.99	22.19	17.83	17.12	16.44	16.77	16.53	19.50	19.38	22.33	25.86
Min	9	13	13	15	17	18	17	15	12	10	11	12	9
Max	150	150	146	146	121	113	108	107	111	111	120	125	136
Skewness		0.995		*p-value*		0.000							
Kurtosis		4.260		*p-value*		0.000							

Table 3.6: Average windspeed

Relative humidity

The relative humidity is a weather factor given in percentages. The percentage is calculated as an average during the 24 hour period of the day. Relative humidity has a mean which is higher during the winter months than compared to summer, which can be seen in Table 3.7. This weather variable is considered to be non-normally distributed as well.

UG	**Total**	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**June**	**July**	**Aug**	**Sept**	**Oct**	**Nov**	**Dec**
Average	80.66	86.82	84.76	79.31	75.10	73.20	74.48	74.60	78.35	81.06	84.56	87.75	88.30
St. Dev	9.46	6.50	8.46	9.43	8.47	10.01	8.31	9.25	6.92	6.52	6.48	5.61	6.15
Min	38	67	52	44	46	48	47	38	54	62	59	68	65
Max	100	99	99	96	96	96	93	95	96	95	97	100	100
Skewness	-0.595		*p-value*		0.000								
Kurtosis	3.272		*p-value*		0.003								

Table 3.7: Relative humidity

CHAPTER 4 Methodology

The method conducted is aimed at testing the second and third hypothesis, as the first hypothesis is already answered in the literature review of chapter 2. Before regressions can be conducted the multicollinearity of the variables is tested by using a VIF test. For a different perspective on multicollinearity the correlation between variables is estimated. To end section 4.1 the heteroskedasticity is tested for all data variables as this is important for further tests conducted on the data. Data transformations are applied to the retrieved data, which is described in section 4.2. First, OLS regression of stock return and trading volume on weather variables are described in section 4.3. Followed by MANOVA multivariate regressions which is explained in section 4.4. And section 4.5 explains the methodology used for the OLS regressions with as independent variable interacted weather variables.

4.1 Multicollinearity and heteroskedasticity

This section describes how multicollinearity is tested. Multicollinearity testing is to guarantee there is no relationship existent among the different weather variables. If the independent variables appear to be correlated the variable coefficients and standard errors will not be estimated correctly. First, a VIF test is conducted. The Variance Inflation Factor is useful for detecting multicollinearity. When the value of the VIF test is greater than 10 this indicates multicollinearity. Additionally a cross correlation table is retrieved for a closer look at the correlation among the relevant variables.

A Breusch-Pagan test is conducted to test whether the data is homoscedastic or heteroskedastic. In case the data is heteroskedastic OLS regressions are run using robust standard errors. This is done to prevent the standard errors from being biased (Hayes & Cai, 2007). As the adjusted R-squared is not included in regressions where robust standard errors are applied the value is calculated by use of the following formula in STATA (Statistics How To, 2013):

$$R_{adj}^2 = 1 - \left(\frac{(1 - R^2)(n - 1)}{n - k - 1}\right)$$

4.2 Data transformations

After the data has been retrieved and tested for multicollinearity and heteroskedasticity, some transformations will are applied to the data observations of temperature. First, the data is sorted by month, per month the average will be calculated, which can be seen in Table 3.4 of section 3.2. The average temperature of the specific month will be subtracted from the temperature that was observed that day during that month. The average temperature per month serves as a guideline for normal circumstances during that specific time of the year. This transformation removes seasonality from the data set. The formula to calculate the average temperature:

$$average\ temperature_t = average\ day\ temperature_t - average\ month\ temperature$$

The outcome of this formula can give positive and negative values. For example, if the temperature is above average, average temperature takes on a positive value. When the temperature is below average, the average temperature is negative. Temperature is said to be affecting the mood of investors and thus causing price changes, leading to biases in investor judgement and behaviour (Kliger & Levy, 2003), thus a negative average temperature value will negatively affect stock returns. Likewise, a positive average temperature positively affects stock returns. The average temperature value, average day temperature minus average month temperature, is used for further analysis in this thesis.

The second data transformation is applied to the AEX data, which consists of opening and closing price. Stock return has a positive value when the stock price increases during the day and a negative value when the stock price decreases. Stock return is calculated by subtracting the logarithm of opening price from the logarithm of closing price of that same day. Thus, in formula:

$$stock\ return_t = \ln closing\ price_t - \ln opening\ price_t$$

4.3 OLS Regressions

The hypotheses are tested by running Ordinary Least Squares (OLS) regressions with as independent variables hours of sunshine, average temperature, duration of rainfall, average windspeed and relative humidity. The dependent variables in the OLS regressions are stock return and trading volume. Standard robust errors are used in case the data is heteroskedastic to provide unbiased estimates on the coefficients and error terms.

In chapter 2 the first hypothesis was answered based on theory. Stock and weather data is analysed to answer the second and third hypothesis, which will be explained in the following sections. The second hypothesis is stated as follows:

"Weather does affect stock returns."

The hypothesis is constructed by smaller hypothesis, one for every weather variable per stock variable. The predicted OLS regression regresses the stock price on the specific weather variable. Based on The linear regression will predict a line which regresses the stock price on the specific weather variable. Based on Table 1.1, established in section 1.2, the OLS regressions are numbered. The corresponding regressions to the hypotheses are:

$$stock\ return_t = \beta_0 + \beta_1 \cdot hours\ of\ sunshine_t + \epsilon_t \tag{2.1}$$

$$stock\ return_t = \beta_0 + \beta_1 \cdot average\ temperature_t + \epsilon_t \tag{2.2}$$

$$stock\ return_t = \beta_0 + \beta_1 \cdot duration\ of\ rainfall_t + \epsilon_t \tag{2.3}$$

$$stock\ return_t = \beta_0 + \beta_1 \cdot average\ windspeed_t + \epsilon_t \tag{2.4}$$

$$stock\ return_t = \beta_0 + \beta_1 \cdot relative\ humidity_t + \epsilon_t \tag{2.5}$$

The β_0 represents the constant, β_1 estimates the value of the coefficient of the specific weather variable and ε_t denotes the corresponding error term.

Likewise the same method is used for investigating the second hypothesis, stated as:

"The weather does influence trading volume."

For every smaller hypothesis of trading volume (Table 1.1) an OLS regression is conducted. The estimated regressions are:

$$trading\ volume_t = \beta_0 + \beta_1 \cdot hours\ of\ sunshine_t + \varepsilon_t \tag{3.1}$$

$$trading\ volume_t = \beta_0 + \beta_1 \cdot average\ temperature_t + \varepsilon_t \tag{3.2}$$

$$trading\ volume_t = \beta_0 + \beta_1 \cdot duration\ of\ rainfall_t + \varepsilon_t \tag{3.3}$$

$$trading\ volume_t = \beta_0 + \beta_1 \cdot average\ windspeed_t + \varepsilon_t \tag{3.4}$$

$$trading\ volume_t = \beta_0 + \beta_1 \cdot relative\ humidity_t + \varepsilon_t \tag{3.5}$$

Again, β_0 is representative for the constant, β_1 indicates the value of the coefficient of the weather variable and ε_t is the corresponding error term.

4.4 MANOVA Multivariate regression

The second test applied to the data to examine the hypotheses on stock returns and trading volume is the MANOVA multivariate regression. In this test the effect of multiple independent variables, in this case the weather variables, can be tested on multiple related dependent variables. Stock returns and trading volume are related as both variables describe the state of the stock market. The weather variables are classified as continuous variables in the regression. The MANOVA multivariate regressions results in the following to regression outputs:

$$\begin{aligned} stock\ return_t \\ &= \beta_0 + \beta_1 \cdot hours\ of\ sunshine + \beta_2 \cdot average\ temperature + \beta_3 \\ &\cdot duration\ of\ rainfall + \beta_4 \cdot average\ windspeed + \beta_5 \\ &\cdot relative\ humidity + \varepsilon_t \end{aligned}$$

$$\begin{aligned} trading\ volume_t \\ &= \beta_0 + \beta_1 \cdot hours\ of\ sunshine + \beta_2 \cdot average\ temperature + \beta_3 \\ &\cdot duration\ of\ rainfall + \beta_4 \cdot average\ windspeed + \beta_5 \\ &\cdot relative\ humidity + \varepsilon_t \end{aligned}$$

Where β_0 represents the constant, the other betas estimate the weather variable coefficients and ε_t is the corresponding error term.

4.5 OLS Regressions with interaction variables

To dive deeper into the weather effect the weather variables are regressed as interaction variables. The five weather variables hours of sunshine, average temperature, duration of rainfall, average windspeed and relative humidity are interacted. The effect of the interaction variables on the dependent variables stock return and trading volume is measured. For both dependent variables a total of 15 different regressions are regressed to discover the significant interaction variables. Robust standard errors are applied in case the data appears to show heteroskedasticity. This is an extension of previous conducted research as the combined effect has not been researched as much as the effect of a single weather variables on stock variables.

CHAPTER 5 Results

The fifth chapter result is divided into different sections based on the methodology described in chapter 4. Section 5.1 discusses the results of multicollinearity and heteroskedasticity, followed by the transformations applied to the data in section 5.2. The results of the OLS regression of stock return and trading volume are discussed in section 5.3 and 5.4. In section 5.5 the MANOVA and multivariate regression outcome is evaluated. And the final section of this chapter will take a look at the OLS regressions of the interaction variables which are significant in affecting stock returns and trading volume.

5.1 Multicollinearity and heteroskedasticity results

In Table 5.1 the outcome of the VIF test for the variables sunshine hours in percentages of the total hours of sunshine, average temperature, duration of rainfall, average windspeed and relative humidity are shown. As all of the values are below 10, there is no sign of multicollinearity.

Variables	**VIF**	**1/VIF**
Sunshine hours (percentage)	1.85	0.540
Average temperature	1.05	0.955
Duration of rainfall	1.39	0.719
Average windspeed	1.26	0.797
Relative Humidity	1.78	0.561
Mean VIF	1.47	

Table 5.1: VIF test on the weather variables

In Table 5.2 a cross correlation table shows the correlation between the different weather variables. The highest correlation is found between the variables sunshine hours as a percentage of the maximum possible hours of sunshine and relative humidity with a value of -0.619. None of these correlation values are considered high enough to suspect multicollinearity.

	Sunshine hours (percentage)	**Average temperature**	**Duration of rainfall**	**Average windspeed**	**Relative Humidity**
Sunshine hours (percentage)	1	0.030	-0.434	-0.231	-0.619
Average temperature	0.030	1	-0.007	0.182	-0.104
Duration of rainfall	-0.434	-0.007	1	0.331	0.376
Average windspeed	-0.231	0.182	0.331	1	-0.014
Relative humidity	-0.619	-0.104	0.376	-0.014	1

Table 5.2: Cross correlation table of the weather variables

The heteroskedasticity was tested for all variables using the Breusch-Pagan test. The outcome of this test can be found in Table 5.3 It shows that all variables except average temperature appeared to have a significant p-value, which means they show heteroskedasticity. Therefore robust standard errors will be used in running OLS regressions.

Variable	$\boldsymbol{Chi^2}$	$\boldsymbol{Prob > Chi^2}$
Stock returns	437.52	0.0000
Volume	1465.82	0.0000
Sunshine hours	14.03	0.0002
Average temperature	0.01	0.9028
Duration of rainfall	6.95	0.0084
Average windspeed	11.27	0.0008
Relative humidity	26.22	0.0000

Table 5.3: Breusch-Pagan test

5.2 Data transformation results

After the data transformations have been applied as described in methodology section 4.2. The first transformation was applied to the average return of a day, which was seasonally adjusted. The distribution of the average temperature histogram has a more standard normal distribution as can be seen in Histogram 5.1.

The second transformation was applied to the opening and closing price, which were combined to create the stock return variable. The graph of the stock return over time can be found in Graph 5.1.

5.3 Stock return results

The OLS regressions of stock return on the weather variables are discussed in this section. The regressions results are located in the appendix in Table 5.4 to Table 5.8. The separate regressions of stock return on the weather variables hours of sunshine (0.727), duration of rainfall (0.880), average windspeed (0.462) and relative humidity (0.701) have a p-value higher than 0.05, which can be seen by their p-value between brackets. The coefficient estimates are not considered significant. Resulting in the null hypothesis which cannot be rejected. The regression of stock return on average temperature (Table 5.5), which is significant on the 5 percent significance level with a p-value of 0.020. The coefficient of average temperature has a negative value of -0.0000119. Thus, even though average temperature has a negative effect on the stock return, this effect is considered to be very small.

Linear regression				**Number of observations**		3,582
				F(1,3580)		5.40
				Prob > F		0.0201
				R-squared		0.0014
				Adjusted R-squared		0.0011
				Root MSE		0.0103
Stock return	**Coefficient**	**Robust Standard Error**	**t**	$P > \|t\|$	**95% Confidence Interval**	
Average temperature	-0.0000119	$5.11e^{-6}$	-2.32	0.020	-0.000219	$-1.86e^{-6}$
Constant	-0.000275	0.000172	-1.60	0.110	-0.000613	0.0000622

Table 5.5: Linear regression of stock return on average temperature

5.4 Trading volume results

This section discusses the outcome of the OLS regressions of trading volume on the weather variables. The regressions are presented in Table 5.9 to Table 5.13. The regressions of trading volume on hours of sunshine (0.057), average temperature (0.493), duration of rainfall (0.067) and relative humidity (0.064) have a p-value higher than 0.05. Their null hypotheses are rejected at the 5% significance level. However, if the significance level of 10% is considered hours of sunshine, duration of rainfall and relative humidity they are concluded significant. The weather variable average windspeed has a p-value of 0.001 and is considered significant, which can be seen in Table 5.12. The null hypothesis that average windspeed does not have a significant effect on trading volume is rejected. The coefficient has a value of 124,323, which means that if windspeed increases by 0.1 m/s trading volume increases by that amount, thus windspeed positively affects trading volume.

Linear regression				**Number of observations**		3,582
				F(1,3580)		11.83
				Prob > F		0.0006
				R-squared		0.0039
				Adjusted R-squared		0.0036
				Root MSE		4.3e+07
Volume	**Coefficient**	**Robust Standard Error**	**t**	$P > \|t\|$	**95% Confidence Interval**	
Average windspeed	124,323	36151.28	3.44	0.001	53,443.88	195,202.20
Constant	$1.04e^{8}$	1,844,921	56.28	0.000	$1.00e^{8}$	$1.07e^{8}$

Table 5.12: Linear regression of trading volume on average windspeed

5.5 MANOVA Multivariate regression results

Table 5.14 presents the MANOVA test command outcome and Table 5.15 displays the corresponding multivariate regressions for both stock returns and trading volume. The MANOVA test (Table 5.14) displays the p-values of all different test statistics for the models. If all four values are below 0.05 they are considered to be significant on the 5% significance level. The four different criteria and their corresponding p-values between brackets are Wilk's lambda (0.0090), Pillai's trace (0.0090), Lawley-Hotelling trace (0.0090) and Roy's largest root (0.0028). The same table presents multivariate test, shown for each weather variable separately. Hours of sunshine (0.8201), duration of rainfall (0.9439) and relative humidity (0.3998) appear not to be significant, but average temperature (0.0468) and average windspeed (0.0017) are significant. Which is in line with the outcome of the OLS regressions of the two previous sections.

Table 5.15 represents the second part of the MANOVA multivariate regression. The p-value of the total model show that the multivariate model of stock returns is not significant due to the p-value of 0.3625. However, the model of trading volume is significant with as p-value of the model 0.0031. The lower part of the table describes the multiple regressions of the stock returns and trading volume on the weather variables.

In the regression of stock returns on weather variables only the variable of average temperature is significant with a p-value of 0.038. And for the regression of trading volume on the weather variables, average windspeed is considered significant with a p-value of 0.000. Thus, in both of the models, only one of the five independent variables is considered to have a significant effect on stock returns or trading volume.

The column $R-sq$ shows that the weather variables only explain 0.15% of the variance in the model on stock returns and 0.5% of the variance in the model of trading volume.

The regressions that can be formed from the multivariate regression table can be written as:

$$\begin{aligned} &stock\ return_t \\ &\quad = -0.00112 + 4.694^{-6} \cdot hours\ of\ sunshine_t - 1.1e^{-5} \\ &\quad \cdot average\ temperature_t + 2.53e^{-6} \cdot duration\ of\ rainfall_t - 2.53e^{-6} \\ &\quad \cdot average\ windspeed_t + 9.22e^{-6} \cdot relative\ humidity_t + \varepsilon_t \end{aligned}$$

$$\begin{aligned} &trading\ volume_t \\ &\quad = 9.3 \cdot e^{7} + 5{,}058.691 \cdot hours\ of\ sunshine_t - 26{,}796.72 \\ &\quad \cdot average\ temperature_t - 677.737 \cdot duration\ of\ rainfall_t + 133{,}569.8 \\ &\quad \cdot average\ windspeed_t + 127{,}077.5 \cdot relative\ humidity_t + \varepsilon_t \end{aligned}$$

5.6 OLS Regression with interaction variables results

The extend previous conducted research the effect of interaction variables on the weather is taken into account in the following regressions. For both stock returns and trading volume the interaction variables are established and regressions are run, which leads to a total of 30 regressions. An overview is made in Table 5.16 and 5.17 to see which combinations are significant. The corresponding p-values of the regressions are expressed in the coloured boxes which indicate the significant regressions. The OLS regressions of the significant regressions can be found in Table 5.18 to Table 5.25. Stock returns has two significant regressions with the interaction variables AverageTemperature*DurationRainfall and RelativeHumidity*AverageTemperature. Trading volume does have six significant regressions with the interaction variables RelativeHumidity*RelativeHumidity, RelativeHumidity*SunshineHours, RelativeHumidity*AverageTemperature, RelativeHumidity*DurationRainfall, DurationRainfall*SunshineHours and SunshineHours*SunshineHours. The only interaction variable which has a significant effect on both stock returns and trading volume is RelativeHumidity*AverageTemperature. Another conclusion following from these regressions is that the interaction variables of relative humidity have the most significant regressions for trading volume. Three of the five interaction variables with relative humidity that are significant, have a negative effect on stock returns or trading volume.

Stock returns	**Hours of sunshine**	**Average temperature**	**Duration of rainfall**	**Average windspeed**	**Relative humidity**
Hours of sunshine					
Average temperature			0.032		0.017
Duration of rainfall		0.032			
Average windspeed					
Relative humidity		0.017			

Table 5.16: Stock return significant interaction variable regressions

Trading volume	**Hours of sunshine**	**Average temperature**	**Duration of rainfall**	**Average windspeed**	**Relative humidity**
Hours of sunshine	0.007		0.007		0.006
Average temperature					0.035
Duration of rainfall	0.007				0.013
Average windspeed					
Relative humidity	0.006	0.035	0.013		0.003

Table 5.17: Trading volume significant variable regressions

CHAPTER 6 Conclusion

The aim of the research was to look at whether investor behaviour is influenced by the weather conditions by answering the constructed research question:

Does the weather effect exist in the Amsterdam Stock Exchange?

The research question is based on three hypotheses. The first hypothesis is stated as:

The weather has effect on investor behaviour.

The first part of the hypothesis is solved theoretically. Multiple earlier conducted researches, mainly psychological researches, investigated how people react to weather conditions. It is concluded that indeed the mood of an investor, caused by the weather, leads to different choices being made. However, some people react more sensitive to the weather as others. This can be dependent on time spent outside or a seasonal affective disorder (Keller et al., 2005). As a result of the weather investors can be more optimistic or pessimistic when deciding on an investment.

The second and third hypotheses directed at investigating how the weather does affect the stock prices and trading volume:

The weather does affect stock return.

The weather does influence trading volume.

For both stock prices and trading volume five regressions were conducted, thus a total of ten OLS regressions. However, only two OLS regressions appeared to be significant. The two that were significant were stock return on average temperature and trading volume on average windspeed. Average temperature negatively affected stock returns, however, this was only a small effect. This conclusion is in line with the research conducted by Floros (2008). He found a negative relationship between the returns of the stock market and temperature in Austria, Belgium and France. The same conclusion is found by Cao and Wei (2004) who discovered this relationship in eight different countries spread over all continents. The OLS regression of this thesis conducts a positive relationship between average windspeed and trading volume. All of the other regressions appeared not to be significant. Thus, a clear relationship between the weather and stocks cannot be confirmed.

In the MANOVA multivariate regression it became clear that the model on trading volume was significant however the model of the effect of multiple variables on stock returns was not.

Interaction variables of the weather variables lead to more significant OLS regressions. However, similar to the MANOVA regression outcome, the OLS regressions with stock return as dependent variable had less significant regressions than trading volume had.

A significant weather effect cannot be concluded from this thesis. Even though some weather and interaction variables appeared to be significant, a lot of the regressions and tests also were not significant. The variables which seemed to have the biggest effect were average temperature on stock returns and average windspeed on trading volume. With interaction variables average windspeed combined with other weather variables had the most significant relationships and is therefore considered an important weather variable as well.

CHAPTER 7 Discussion

In this chapter the reliability of the data, methodology, results and conclusion are evaluated. Different factors affect the outcome of the research which may lead to doubts about the thesis. The weak points of the conducted data and methodology are discussed and followed by recommendations for further research.

7.1 Discussion on data

The AEX stock data contains stocks of large market capitalization companies. However, the weather effect as a stock market anomaly is considered to be a local influence. Therefore, using data on the AMX or AScX would give a more local representation of the stock market. These stocks indexes are mid and small capitalizations focussing on more local stock companies. The weather effect might have more apparent effect on these type of stocks.

Another point of discussion on the data is that when taking a larger sample of data, meaning a longer period, the weather effect might have been found. This is because the last couple of years investing is done more often by making use of algorithms and computer models. Investors could not have been influenced by the weather as this does not have effect on the investments being done. Thus, by analysing a longer period, it might have been possible to find the weather effect in the earlier years of the sample.

7.2 Discussion on methodology

Some points for discussion on the methodology used in this thesis are encountered in this section. Whether other methods would be more relevant, or lead to other conclusions cannot be said.

The first point for discussion is whether the data should have been corrected for stock market anomalies. Previously conducted researches did correct for one stock market anomaly, however the papers all did correct for their own chosen calendar effect. This thesis is unable to encompass the entire range of existing stock market anomalies. Whether including discovered anomalies in the research would have led to better outcomes cannot be said.

Another potential problem is that the previous day stock return is not incorporated into the regressions but some related previously conducted researched did incorporate these into the regressions. It is beyond the scope of this thesis to examine the effects of variables other than those of the weather on the stock returns and trading volume.

7.3 Recommendations for further research

Recommendations for further research are based on the discussion points mentioned in the previous two sections. Recommendations thus for further research can be summed up as:

- Focussing on a different stock index. Looking at a local stock market instead of a large capitalization stock market the weather effect might become more apparent.
- Using a larger sample to investigate the existence of the weather effect can improve the conclusion. By taking a larger sample period the reaction of the market to the weather conditions over time can be investigated and compared.
- Incorporating all other stock market anomalies to make sure stock prices are not influenced by already discovered anomalies.
- Including more relevant variables into regressions which explain the stock return and trading volume.

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Data used on the variables:

- 24-hour average temperature
- Percentage of sunshine hours from longest possible length
- Duration of rainfall
- Average windspeed
- Relative humidity

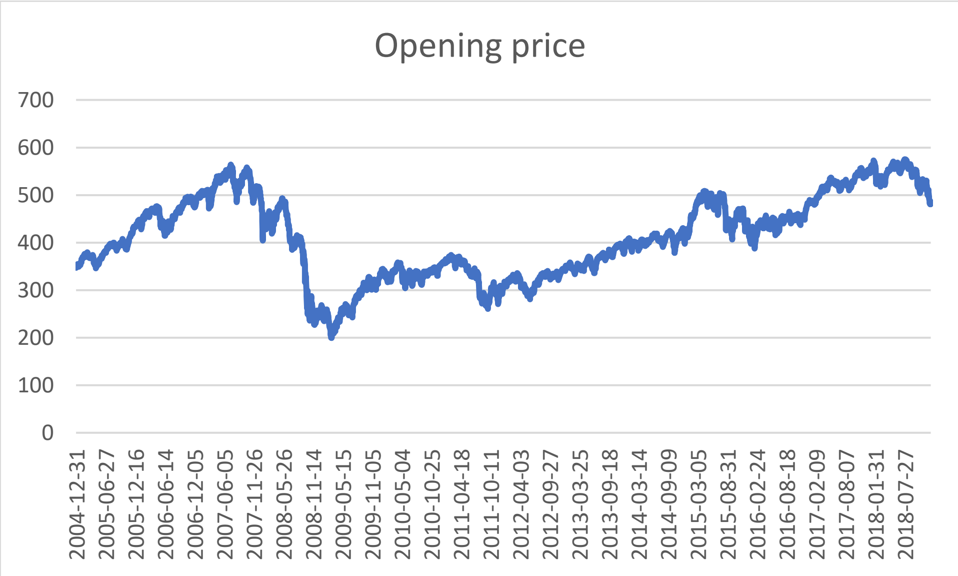
Yahoo! Finance. Data retrieved from the AEX-Index from:
https://finance.yahoo.com/quote/%5EAEX/history

Data used on the variables:

- Opening price
- Closing price
- Trading volume

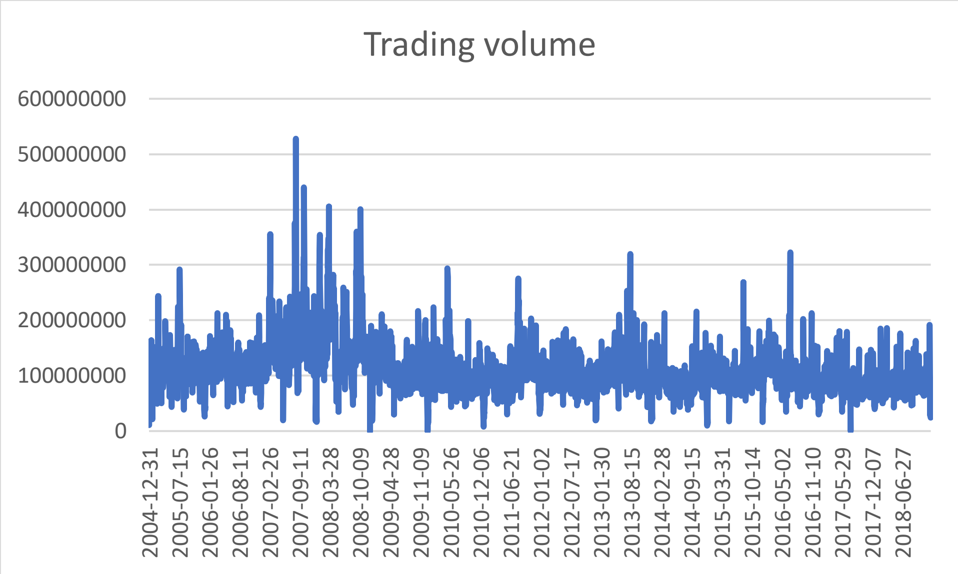
APPENDIX Graphs

Graphs Chapter 3



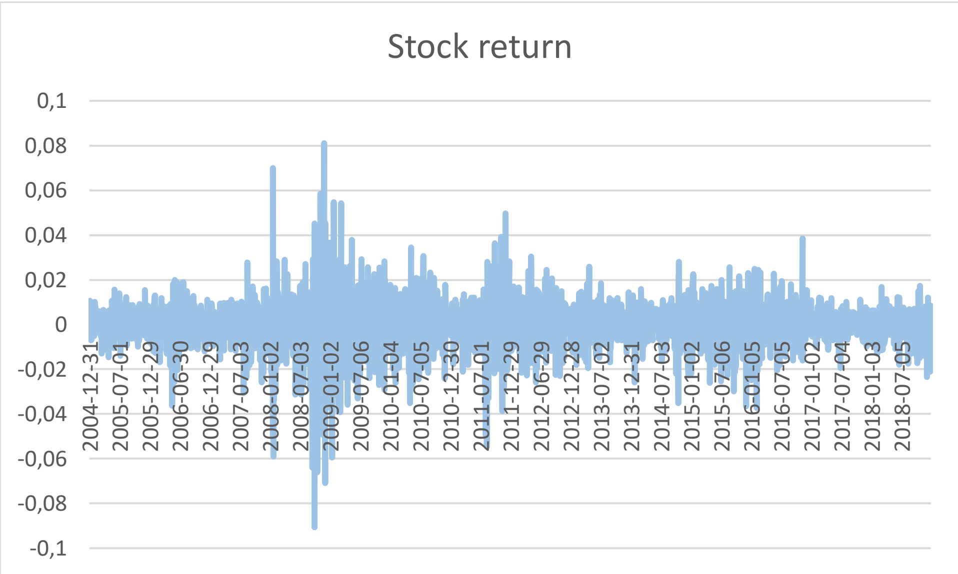
Graph 3.1: Opening price over time

Graph 3.2: Closing price over time



Graph 3.3: Trading volume over time

Graphs Chapter 5



Graph 5.1: Stock return over time

APPENDIX Tables

Tables Chapter 1

Does the weather effect exist in the Amsterdam Stock Exchange?	
1 The weather has effect on investor behaviour.	
	1.1 Weather conditions do affect mood.
	1.2 Emotions do affect decision-making.
2 The weather does affect stock returns.	
	2.1 Hours of sunshine has a positive correlation with the prices of equity.
	2.2 The average temperature of the day has a positive correlation with stock prices
	2.3 The duration of rainfall during the day is negatively correlated with stock prices.
	2.4 The stock prices are negative affected by the local windspeed.
	2.5 Relative humidity does negatively affect the stock prices.
3 The weather does influence trading volume	
	3.1 Hours of sunshine has a positive effect on the volume that is traded.
	3.2 The average temperature fluctuations will lead to trading volume differences.
	3.3 The duration of rainfall will be negatively correlated to the trading volume.
	3.4 Windspeed does have a negative effect on trading volume.
	3.5 Relative humidity is negatively correlated with trading volume.

Table 1.1: Overview central research question and corresponding hypotheses

Tables Chapter 3

Variable	Explanation	Unit
Opening price	Price of stock at beginning of the day	Euros
Closing price	Price of stock at the end of the day	Euros
Trading volume	Amount of stocks traded	-
Hours of sunshine	Hours of sunshine as a percentage of the maximum hours of sunshine	Percentage
Average temperature	Average temperature of the day over a 24-hour period	0.1 degrees Celsius
Duration of rainfall	Duration of rainfall of the day over a 24-hour period	0.1 hours
Average windspeed	Average windspeed of the day over a 24-hour period	0.1 m/s
Relative humidity	Relative humidity during the day over a 24-hour period	Percentages

Table 3.1: Variable descriptions

Tables Chapter 5

Linear regression				**Number of observations**		3,582
				F(1,3580)		0.12
				Prob > F		0.7272
				R-squared		0.0000
				Adjusted R-squared		-0.0002
				Root MSE		0.0103
Stock return	**Coefficient**	**Robust Standard Error**	**t**	$P > \|t\|$	**95% Confidence Interval**	
Hours of sunshine	$1.91e^{-6}$	$5.49e^{-6}$	0.35	0.727	$-8.84e^{-6}$	0.0000127
Constant	-0.000349	0.000287	-1.22	0.224	-0.000911	0.000213

Table 5.4: Linear regression of stock return on hours of sunshine

Linear regression					**Number of observations**	3,582
					F(1,3580)	0.00
					Prob > F	0.8800
					R-squared	0.0000
					Adjusted R-squared	-0.0003
					Root MSE	0.0103
Stock return	**Coefficient**	**Robust Standard Error**	**t**	$\boldsymbol{P > \lvert t \rvert}$	**95% Confidence Interval**	
Duration of rainfall	$9.50e^{-7}$	$6.29e^{-6}$	0.15	0.880	-0.0000114	0.0000133
Constant	-0.000291	0.000196	-1.49	0.137	-0.000675	0.0000929

Table 5.6: Linear regression of stock return on duration of rainfall

Linear regression					**Number of observations**	3,582
					F(1,3580)	0.54
					Prob > F	0.4623
					R-squared	0.0002
					Adjusted R-squared	-0.0001
					Root MSE	0.0103
Stock return	**Coefficient**	**Robust Standard Error**	**t**	$\boldsymbol{P > \lvert t \rvert}$	**95% Confidence Interval**	
Average windspeed	$-6.14e^{-6}$	$8.35e^{-6}$	-0.74	0.462	-0.0000225	0.000102
Constant	0.000255	0.000441	0.06	0.954	-0.000840	0.000891

Table 5.7: Linear regression of stock return on average windspeed

Linear regression					**Number of observations**	3,582
					F(1,3580)	0.15
					Prob > F	0.7014
					R-squared	0.0000
					Adjusted R-squared	-0.0002
					Root MSE	0.0103
Stock return	**Coefficient**	**Robust Standard Error**	**t**	$\boldsymbol{P > \lvert t \rvert}$	**95% Confidence Interval**	
Relative humidity	$6.93e^{-6}$	0.0000181	0.38	0.701	-0.0000285	0.0000424
Constant	-0.000834	0.00143	-0.58	0.560	-0.00364	0.00197

Table 5.8: Linear regression of stock return on relative humidity

Linear regression				Number of observations	3,582	
				F(1,3580)	3.62	
				Prob > F	0.0570	
				R-squared	0.0009	
				Adjusted R-squared	0.0006	
				Root MSE	4.3e+07	
Volume	**Coefficient**	**Robust Standard Error**	**t**	$P > \|t\|$	**95% Confidence Interval**	
Hours of sunshine	-42,781.08	22,472.91	-1.90	0.057	-86,842.07	1,279.91
Constant	$1.12e^{8}$	1,153,405	96.73	0.000	$1.09e^{8}$	$1.14e^{8}$

Table 5.9: Linear regression of trading volume on hours of sunshine

Linear regression				Number of observations	3,582	
				F(1,3580)	0.47	
				Prob > F	0.4927	
				R-squared	0.0001	
				Adjusted R-squared	-0.0002	
				Root MSE	4.3e+07	
Volume	**Coefficient**	**Robust Standard Error**	**t**	$P > \|t\|$	**95% Confidence Interval**	
Average temperature	-14,382.06	20,960.43	-0.69	0.493	-55,477.64	26,713.52
Constant	$1.10e^{8}$	711,906.90	154.41	0.000	$1.09e^{8}$	$1.11e^{8}$

Table 5.10.: Linear regression of trading volume on average temperature

Linear regression				Number of observations	3,582	
				F(1,3580)	3.35	
				Prob > F	0.0674	
				R-squared	0.0010	
				Adjusted R-squared	0.0007	
				Root MSE	4.3e+07	
Volume	**Coefficient**	**Robust Standard Error**	**t**	$P > \|t\|$	**95% Confidence Interval**	
Duration of rainfall	48,219.97	26,360.32	1.83	0.067	-3,462.79	99,902.72
Constant	$1.09e^{8}$	814,288.10	134.01	0.000	$1.08e^{8}$	$1.11e^{8}$

Table 5.11: Linear regression of trading volume on duration of rainfall

Linear regression				**Number of observations**		3,582
				F(1,3580)		3.42
				Prob > F		0.0643
				R-squared		0.0007
				Adjusted R-squared		0.0004
				Root MSE		4.3e+07
Volume	**Coefficient**	**Robust Standard Error**	**t**	$P > \|t\|$	**95% Confidence Interval**	
Relative humidity	121,383.6	65,588.88	1.85	0.064	-7,211.753	249,978.90
Constant	1.00e^8	5,270,075	19.00	0.000	8.98e^7	1.10e^8

Table 5.13: Linear regression of trading volume on relative humidity

MANOVA		Number of obs		3,581		
	W = Wilks' lambda			**L = Lawley-Hotelling trace**		
	P = Pillai's trace			**R = Roy's largest root**		
Source	**Statistic**	**df**	**F(df1,**	**df2) =**	**F**	**Prob > F**
Model	W 0.9934	5	10.0	7148.0	2.35	0.0090
	P 0.0066		10.0	7150.0	2.35	0.0090
	L 0.0066		10.0	7146.0	2.36	0.0090
	R 0.0051		5.0	3575.0	3.63	0.0028
Residual		3575				
Hours of sunshine	W 0.9999	1	2.0	3574.0	0.20	0.8201 e
	P 0.0001		2.0	3574.0	0.20	0.8201 e
	L 0.0001		2.0	3574.0	0.20	0.8201 e
	R 0.0001		2.0	3574.0	0.20	0.8201 e
Average temperature	W 0.9983	1	2.0	3574.0	3.06	0.0468 e
	P 0.0017		2.0	3574.0	3.06	0.0468 e
	L 0.0017		2.0	3574.0	3.06	0.0468 e
	R 0.0017		2.0	3574.0	3.06	0.0468 e
Duration of rainfall	W 1.0000	1	2.0	3574.0	0.00	0.9439 e
	P 0.0000		2.0	3574.0	0.00	0.9439 e
	L 0.0000		2.0	3574.0	0.00	0.9439 e
	R 0.0000		2.0	3574.0	0.00	0.9439 e
Average windspeed	W 0.9964	1	2.0	3574.0	6.38	0.0017 e
	P 0.0036		2.0	3574.0	6.38	0.0017 e
	L 0.0036		2.0	3574.0	6.38	0.0017 e
	R 0.0036		2.0	3574.0	6.38	0.0017 e
Relative humidity	W 0.9995	1	2.0	3574.0	0.92	0.3998 e
	P 0.0005		2.0	3574.0	0.92	0.3998 e
	L 0.0005		2.0	3574.0	0.92	0.3998 e
	R 0.0005		2.0	3574.0	0.92	0.3998 e
Residual		3575				
Total		3580				

Table 5.14: MANOVA regression stock returns and trading volume on weather variables

Multivariate regression							
Equation	**Obs**	**Parms**	**RMSE**	**"$R-sq$"**	**F**	**P**	**Adj R^2**
Return	3,581	6	0.0103	0.0015	1.092	0.3625	0.00013
Volume	3,581	6	$4.25e^7$	0.0050	3.582	0.0031	0.00359

	Coefficient	**Standard error**	**T**	**$P > \|t\|$**	**95% confidence interval**	
Return						
Hours of sunshine	4.694^{-6}	$7.87e^{-6}$	0.60	0.551	-0.0000107	0.0000201
Average temperature	-0.0000114	$5.49e^{-6}$	-2.08	0.038	-0.0000222	-$6.39e^{-7}$
Duration of rainfall	$2.53e^{-6}$	$7.44e^{-6}$	0.34	0.734	-0.0000121	0.0000171
Average windspeed	-$2.53e^{-6}$	$9.06e^{-6}$	-0.28	0.780	-0.0000203	0.0000152
Relative humidity	$9.22e^{-6}$	0.0000243	0.38	0.704	-0.0000384	0.0000569
Constant	-0.00112	0.00228	-0.49	0.624	-0.00559	0.00336
Volume						
Hours of sunshine	5,058.691	32,478.35	0.16	0.876	-58,619.27	68,636.65
Average temperature	-26,796.72	22,674.79	-1.18	0.237	-71,253.55	17,660.11
Duration of rainfall	-677.737	30,719.37	-0.02	0.982	-60,908.16	59,552.69
Average windspeed	133,569.8	37,394.37	3.57	0.000	60,253.31	206,886.2
Relative humidity	127,077.5	100,327	1.27	0.205	-69,626.33	323,781.4
Constant	$9.3e^7$	9,420,280	9.87	0.000	$7.45e^7$	$1.11e^8$

Table 5.15: Multivariate regression stock returns and trading volume on weather variables

Linear regression				Number of observations	3,581	
				F(3,3577)	2.86	
				Prob > F	0.0355	
				R-squared	0.0027	
				Adjusted R-squared	0.0019	
				Root MSE	0.01029	
Stock return	**Coefficient**	**Robust Standard Error**	**t**	$P > \|t\|$	**95% Confidence Interval**	
Average temperature	-5.43e^{-6}	5.44e^{-6}	-1.00	0.319	-0.0000161	5.25e^{-6}
Duration of rainfall	-1.34e^{-6}	6.35e^{-6}	-0.02	0.983	-0.0000126	0.0000123
Average temperature * Duration of rainfall	-4.38e^{-7}	2.04e^{-7}	-2.15	0.032	-8.37e^{-7}	-3.82e^{-8}
Constant	-0.000275	0.000196	-1.40	0.161	-0.000660	0.000110

*Table 5.18: Stock return on interaction variable average temperature * duration of rainfall*

Linear regression				Number of observations	**3,582**	
				F(3,3578)	**2.97**	
				Prob > F	**0.0308**	
				R-squared	**0.0027**	
				Adjusted R-squared	**0.0019**	
				Root MSE	**0.01029**	
Stock return	**Coefficient**	**Robust Standard Error**	**t**	$P > \|t\|$	**95% Confidence Interval**	
Relative humidity	0.0000674	0.000032	2.09	0.037	4.17e^{-6}	0.000131
Average temperature	7.15e^{-6}	0.0000186	0.39	0.700	-0.0000293	0.0000436
Relative humidity* average temperature	-1.01e^{-6}	4.20e^{-6}	-2.39	0.017	-1.83e^{-6}	-1.82e^{-7}
Constant	-0.000884	0.00148	-0.60	0.549	-0.00378	0.00201

*Table 5.19: Stock return on interaction variable relative humidity * average temperature*

Linear regression				Number of observations	3,581
				F(3,3578)	4.08
				Prob > F	0.0067
				R-squared	0.0023
				Adjusted R-squared	0.0015
				Root MSE	$4.3e^{7}$
Volume	**Coefficient**	**Robust Standard Error**	**t**	$P > \|t\|$	**95% Confidence Interval**	
Hours of sunshine	-485,484.6	184,333.4	-2.63	0.008	-846,893.7	-124,075.4
Relative humidity	-209,050.6	143,096	-1.46	0.144	-489,608.4	71,507.25
Hours of sunshine * Relative humidity	5,601.882	2,258.965	2.48	0.013	1,172.894	10,030.87
Constant	$1.29e^{8}$	$1.24e^{7}$	10.42	0.000	$1.05e^{8}$	$1.53e^{8}$

*Table 5.20: Trading volume on interaction variable hours of sunshine * relative humidity*

Linear regression				Number of observations	3,582
				F(3,3579)	7.58
				Prob > F	0.0005
				R-squared	0.0024
				Adjusted R-squared	0.0018
				Root MSE	$4.3e^{7}$
Volume	**Coefficient**	**Robust Standard Error**	**t**	$P > \|t\|$	**95% Confidence Interval**	
Relative Humidity	2,283,061	712,551.1	3.20	0.001	886,014.2	3,680,108
Relative Humidity* Relative Humidity	-13,884.18	4,640.028	-2.99	0.003	-22,981.54	-4,786.814
Constant	$1.73e^{7}$	$2.70e^{7}$	0.64	0.521	$-3.56e^{7}$	$7.03e^{7}$

*Table 5.21: Trading volume on interaction relative humidity * relative humidity*

Linear regression				Number of observations	3,582	
				F(3,3578)	3.15	
				Prob > F	0.0241	
				R-squared	0.0016	
				Adjusted R-squared	0.0008	
				Root MSE	$4.3e^{7}$	
Volume	**Coefficient**	**Robust Standard Error**	**t**	$P > \|t\|$	**95% Confidence Interval**	
Average temperature	-274,245.7	123,034.5	-2.23	0.026	-515,470.6	-33,020.81
Relative humidity	102,999.5	66,954.92	1.54	0.124	-28,274.09	234,273.2
Average temperature * Relative humidity	3,345.377	1,589.47	2.10	0.035	229.0187	6,461.735
Constant	$1.02e^{8}$	5,395,987	18.85	0.000	$9.11e^{7}$	$1.12e^{8}$

*Table 5.22: Trading volume on interaction average temperature * relative humidity*

Linear regression				Number of observations	3,581	
				F(3,3577)	3.98	
				Prob > F	0.0077	
				R-squared	0.0030	
				Adjusted R-squared	0.0021	
				Root MSE	$4.3e^{7}$	
Volume	**Coefficient**	**Robust Standard Error**	**t**	$P > \|t\|$	**95% Confidence Interval**	
Duration of rainfall	944,498	337,661.1	2.80	0.005	282,470.4	1,606,526
Relative humidity	141,401	72,162.97	1.96	0.050	-83.67083	282,885.7
Duration of rainfall* Relative humidity	-10,277.27	3,771.52	-2.72	0.006	-17,671.81	-2,882.721
Constant	$9.76e^{7}$	5,679,181	17.18	0.000	$8.64e^{7}$	$1.09e^{8}$

*Table 5.23: Trading volume on interaction duration of rainfall * relative humidity*

Linear regression				Number of observations		3,581
				F(3,3577)		4.21
				Prob > F		0.0055
				R-squared		0.0036
				Adjusted R-squared		0.0028
				Root MSE		$4.3e^{7}$
Volume	**Coefficient**	**Robust Standard Error**	**t**	$P > \|t\|$	**95% Confidence Interval**	
Hours of sunshine	-50,619.81	25,280.57	-2.00	0.045	-100,185.6	-1,054.034
Duration of rainfall	-16,830.57	32,770.7	-0.51	0.608	-81,081.7	47,420.55
Hours of sunshine * Duration of rainfall	4,117.035	1,521.733	2.71	0.007	1,133.482	7,100.587
Constant	$1.11e^{8}$	1,458,180	76.09	0.000	$1.08e^{8}$	$1.14e^{8}$

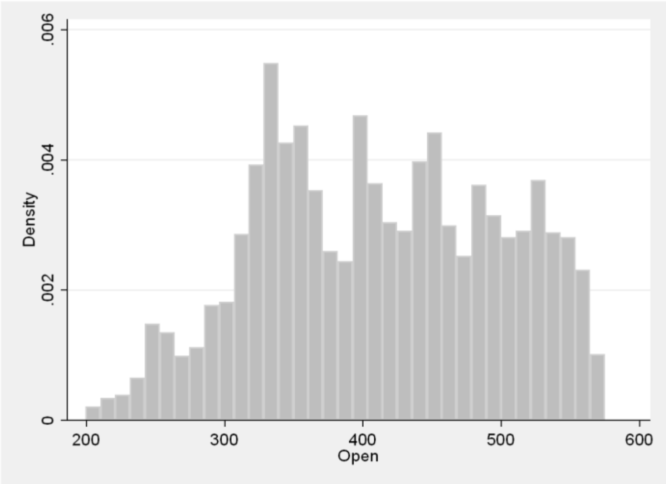
*Table 5.24: Trading volume on interaction hours of sunshine * duration of rainfall*

Linear regression				Number of observations		3,582
				F(2,3579)		6.33
				Prob > F		0.0018
				R-squared		0.0028
				Adjusted R-squared		0.0022
				Root MSE		$4.3e^{7}$
Volume	**Coefficient**	**Robust Standard Error**	**t**	$P > \|t\|$	**95% Confidence Interval**	
Hours of sunshine	171,937.3	86,073.98	2.00	0.046	3,178.345	340,696.3
Hours of sunshine * Hours of sunshine	-2,530.93	941.0134	-2.69	0.007	-4,375.907	-685.9541
Constant	$1.09e^{8}$	1,451,037	75.32	0.000	$1.06e^{8}$	$1.12e^{8}$

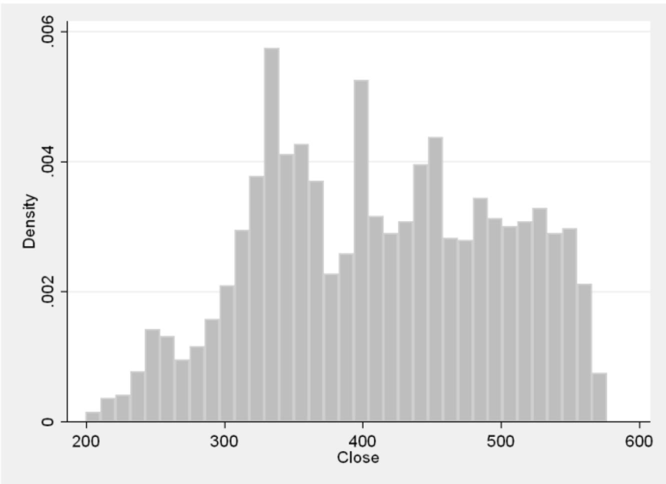
*Table 5.25: Trading volume on interaction hours of sunshine * hours of sunshine*

APPENDIX Histograms

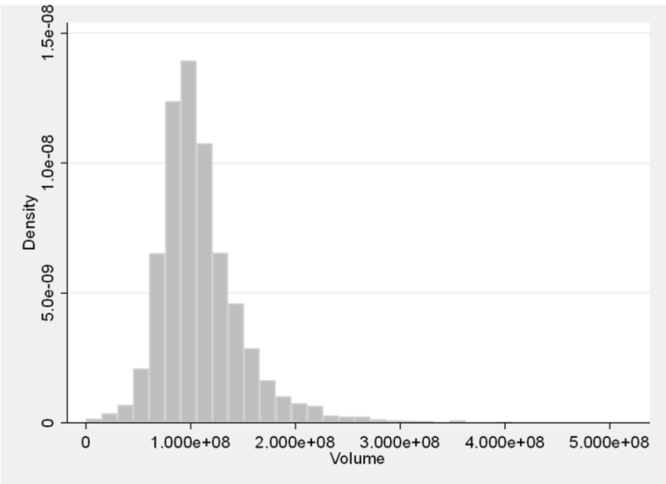
Histograms Chapter 3



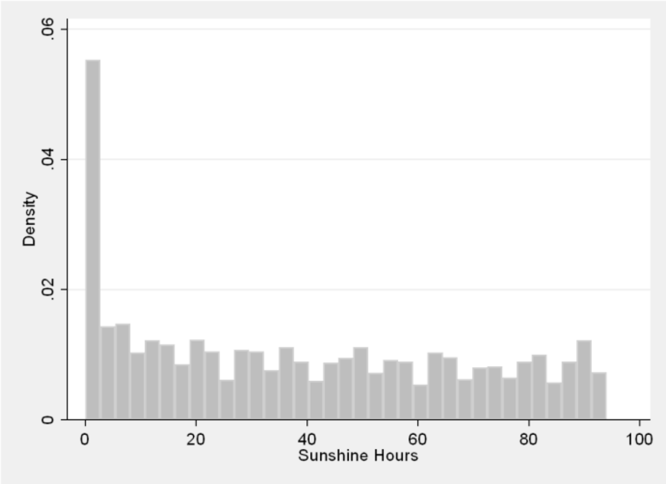
Histogram 3.1: Opening price



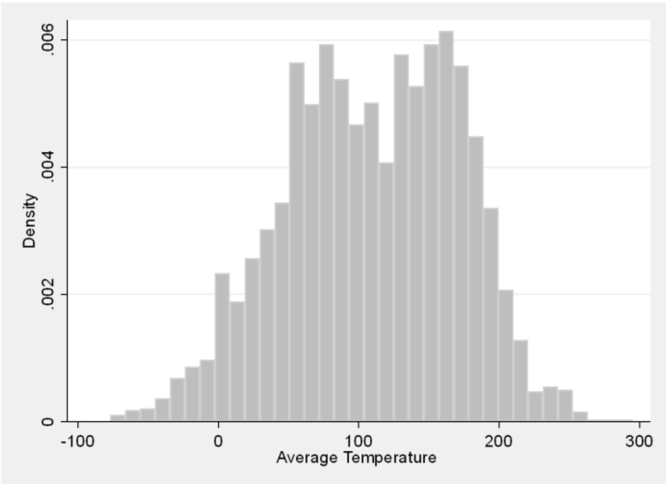
Histogram 3.2: Closing price



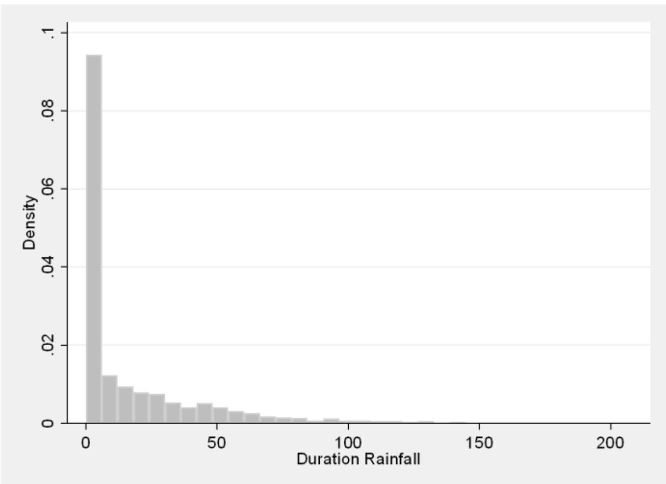
Histogram 3.3: Trading volume



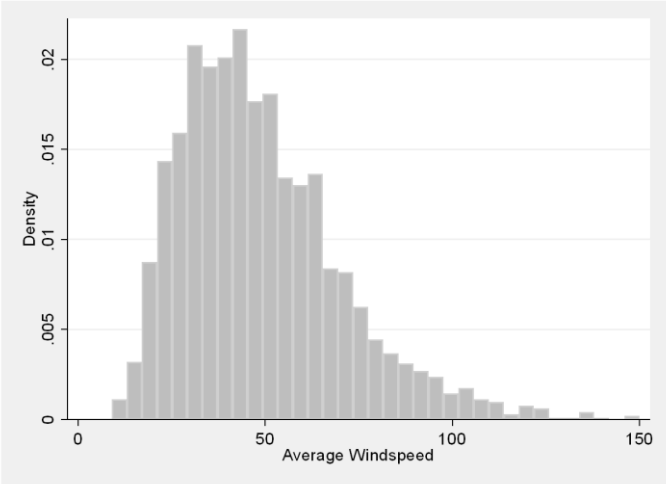
Histogram 3.4: Hours of sunshine



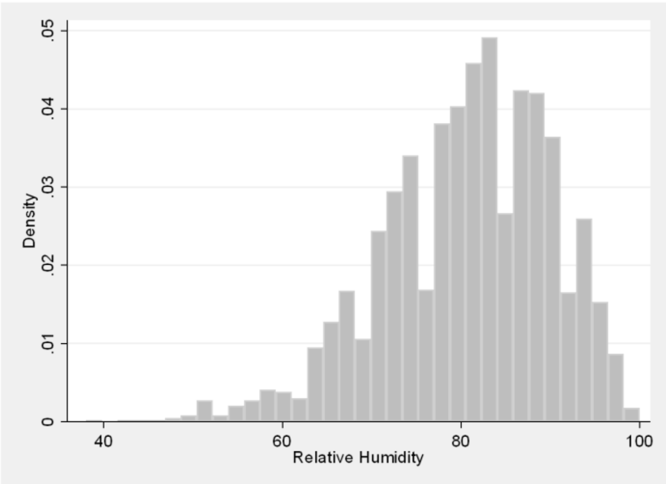
Histogram 3.5: Average temperature



Histogram 3.6: Duration of rainfall

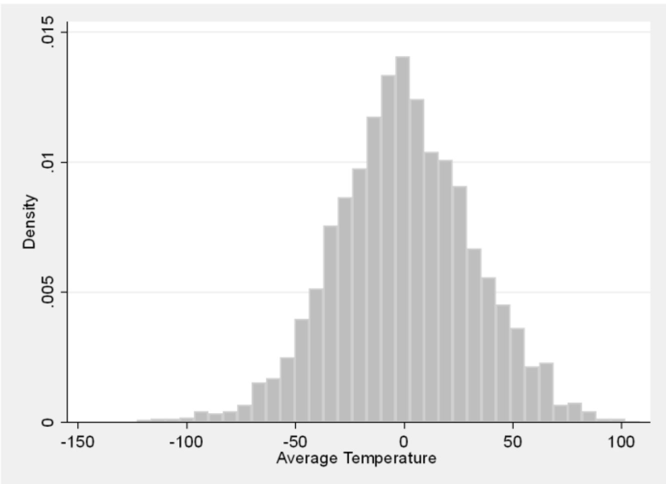


Histogram 3.7: Average windspeed



Histogram 3.8: Relative humidity

Histograms Chapter 5



Histogram 5.1: Average temperature with seasonal adjustment