Trading and Market Microstructure

Term paper

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Bad weather - Bad business?

Weather effects on the German stock market

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Introduction

Every morning for most people there is one same situation: Before people leave their house and decide to go by bus or by bike the first thing they do is to check the weather by looking outside of the window or checking the weather via app. This fact makes it obvious that weather is important for our decision making and mood. But which decisions are influenced by the weather? Does the weather also influence the investors' decisions and therefore has an impact on the stock market?

In this term paper we want to go into the matter if the stock market is influenced by weather. We decided to focus on the German DAX index, because in other studies they analyse several cities and until now none of these studies payed attention to the German DAX index. This topic is very exciting and complex to analyse as many researches have shown. Due to the fact that there are many different research results we want to form our own opinion.

First we want to summarize the current state of research. Afterwards we will have a look at the data we used in our model. Then we particularize our linear regression model that considers different weather parameters. With the model we try to find out if the weather parameters affect the daily stock price changes of the DAX. Finally, we continue with our findings and try to give reasons for our findings and possible explanations.

1. State of research

First we want to present the current state of research relating to the effect of weather on the mood.

Howarth and Hoffmann (1984) found out that people's optimism is increasing in the hours of sunshine a day. Moreover, another result of their research is that weather changes have an effect on most mood dimensions, for instance optimism, anxiety and scepticism (Howarth, E. & Hoffmann, M. 1984; Spasova, Z. 2012). Additionally, research has shown that people trade more often when they are in a good mood and therefore the psychology of investors affects the stock market (Saunders, E. M. 1993; Symeonidis, L., Daskalakis, G. & Markellos, R. 2010; Frühwirth, M. & Sögner, L. 2015).

Because of these findings researchers assumed that there might be a direct relation between the weather and the stock market. For this reason, diverse journals try to figure out if the weather has an effect on the stock market.

The results of the researchers are divided: Some found out that the weather has an indirect impact on the stock market. Whereas other studies came to the conclusion, that there exists no significant relation.

Saunders (1993) was one of the first who saw a causal linkage between weather and the stock market in New York. He advances the view that the weather impact on the stock market is an indirect one, because our mood is important for the decisions at the stock market. Additionally, people's mood is affected by the weather as several psychological studies have shown. This means that you can find a connection between the weather and the stock market. For his research Saunders used local weather data of New York City from 1927 until 1989. In his model he focused on the weather variable cloud cover. By using a regression, he also makes use of three different variables (Dow Jones Industrial Average index (DJI), equal- and value-weighted New York Stock Exchange index (NYSE)) which represent the percentage changes in the stock market each day.

In 2010 Symeonidis et al. supported Saunders findings, because their own analysis resulted in a relationship between the DJI Index and the local weather of New York City. Moreover, they observed that investors are willing to make riskier investments on sunny days. This can be explained due to the fact that sunny weather makes people more optimistic and therefore sun reduces people's risk aversion (Frühwirth, M. & Sögner, L. 2015).

Hirshleifer and Shumway (2003) demonstrated that sun has a significant effect on the daily stock returns but rain and snow do not influence the stock returns. For their research they analyse the relationship between the weather and the stock returns in 26 countries from 1982 until 1997. They used the hourly collected weather data from the International Surface Weather Observations which means that the data is of a very high quality. For their ordinary least squares regression method they focused on the average cloud cover for every day and on the daily index returns they got from Datastream.

Other researches were not able to find the same results. Based on M. Kaustia's and E. Rantapuska's (2015) results there is just evidence that sunniness has an impact on trading but in their analysis this impact is statistically insignificant. Therefore, their results cannot support the thesis that weather has an impact on the financial market. Nevertheless, this does not mean that the investor's mood or psychology can be left behind.

These diverse results or theses encourage us to make our own analysis to find out which relation we can identify between the weather and the financial market. Therefore, we analyse

the German DAX Index from 2005 to 2015, because we want to focus on a time period that has not been considered yet.

2. Data

In total we collected 2798 data points to perform our regression analysis, consisting of the closing point of the German stock market index DAX for every day from 1.1.2005 until 31.12.2015 and the corresponding "weather" of the same day. We focus on a ten-year time period starting from 2005 for several reasons.

First of all, most studies concerning our issue end with data lines between 2004 and 2007, the one from Saunders was even published in 1993. We wanted to look at the most recent time and check if previous findings are still valid. Related to this is the increase of high frequency trading (HFT) in stock trading. The Deutsche Bank estimated 2011 that the percentage of HFT in the whole equity market in the USA rose from approximately 28% in 2005 to 52% in 2010. We were not able to find a study on the German index but since HFT is a global phenomenon the impact on German stock trading patterns should be quite similar. It is also commonly believed that the trend is going to more algorithm trading than the opposite way. Computers are not influenced by the weather, therefore the weather effects on stock markets should decrease with increasing high frequency trading over the last years. Implying already a reason why our findings might be different than previous ones.

Our data line stops with the end of 2015, because the entities providing the weather data, check and process the raw data they get from their stations to cut out mistakes and anomalies. This is done retroactive for a year, providing latest valid data for the end of 2015. The closing points were given to us by the Karlsruhe Institute of Technology (kit) and are consistent and of high quality. It is the closing value of the DAX in Frankfurt am Main for each day in our dataset. Out of the closing we calculated the daily change (close-to-close), which was the actual piece of interest, our dependent variable. For that we subtracted the value of the day before from the closing value of that day and divided this by the closing value from the day before. This is a common used formula to calculate daily changes in stock pieces and includes overnight changes that happen in the index.

Finding figures for the independent weather variables for the three cities we wanted to focus on was more difficult.

The widest range of data was provided by the „*Deutsche Wetterdienst*" (DWD), which included a wide range of weather factors from temperature to relative humidity for Frankfurt

am Main (station Id 1420)[1] for every day. The DWD itself checks the quality of data. For our time period the data quality was rated 10, what means that the quality check is fully finished and that the data is consistent after WMO-Norms which are widely approved and defined by the *World Meteorological Organization.* The needed data for the weather at the London stock market we got from the met office in the UK, and comes from a station located in Heathrow, the nearest station to the exchange and finance district. The quality was also quite high, only the daily sunshine lacked values for four days, which we then excluded from our analyses. For New York we asked the *National Centers for Environmental Information (NOAA)* to provide us with data. The data we received was for the central park, the closest location to the finance district in New York (Station ID: 94728). They were only able to provide us the minimum and the maximum temperature per day but not a daily average. Furthermore, the values they provided were in Fahrenheit where all other temperature data was in Celsius.

We converted Fahrenheit into Celsius with the formula: $°\mathrm{C} = (°\mathrm{F} - 32) * 5/9$.

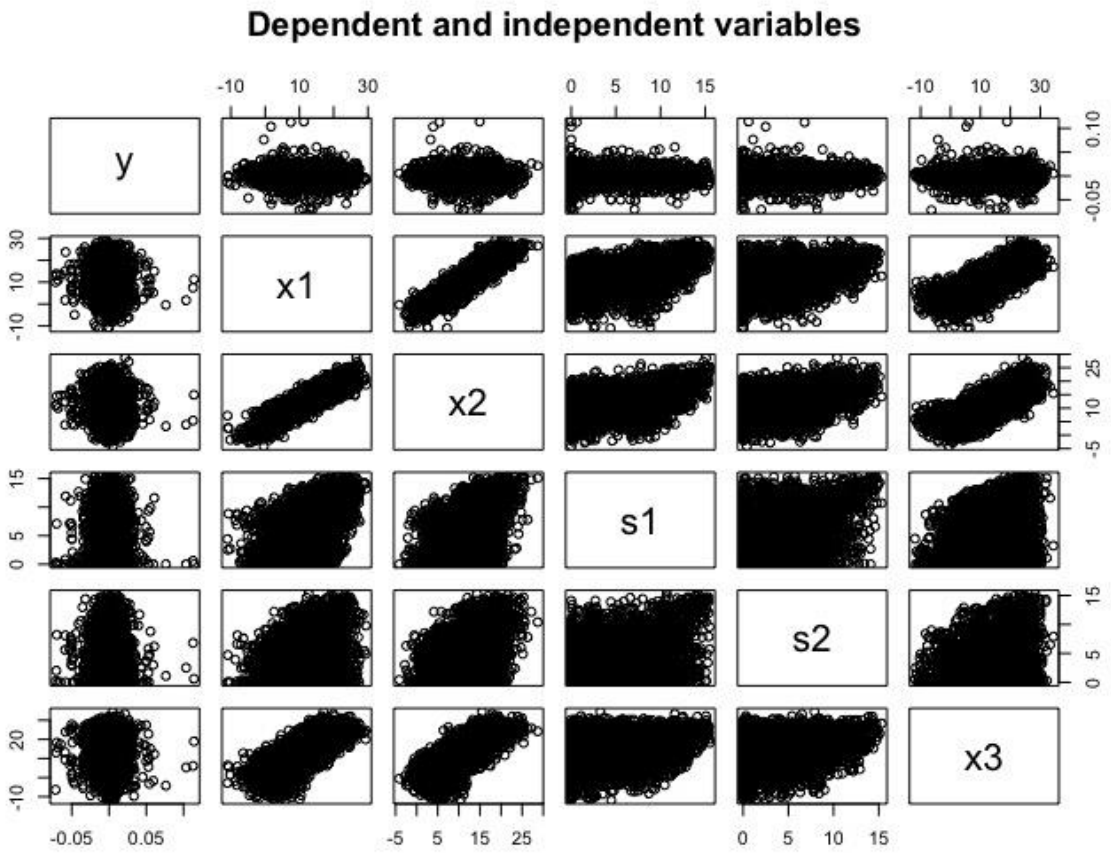
This lack of average temperature per day in the New York data is a weakness in our analyses. The German and English institutes calculated the daily temperature average by taking the temperature hourly dividing it by 24 hours a day. This digit carries more information than the average we calculated for New York. The figure for New York we computed is just the maximum temperature per day, minus the minimum per day divided by two. This calculation is more vulnerable to outliers and not as consistent as the other data sets. Another problem with New York's weather data is that NOAA was not able to provide us with the amount of sun hours per day for the time period neither was there another institution with such information. This makes it harder to find an influence between sunlight and stock market changes, because we are not able to find a connection between sunlight in New York and the influence on German stock prices of that, neither can we apply a model where we consider the daily changes to be influenced by changes in daily sunshine in all three cities together, such as we include the temperature in all three cities in one of our models.

Hirshleifer and Shumway (2003) adjust in their model every daily cloud cover value by a correction factor calculated out of the weeks mean, the to be adjusted value is from. We do that with neither the temperature nor the sunshine per day, because we assume that the human mood is affected by the weather that appears the day and this is neither changed nor

[1] For further information about the station go to: www.dwd.de

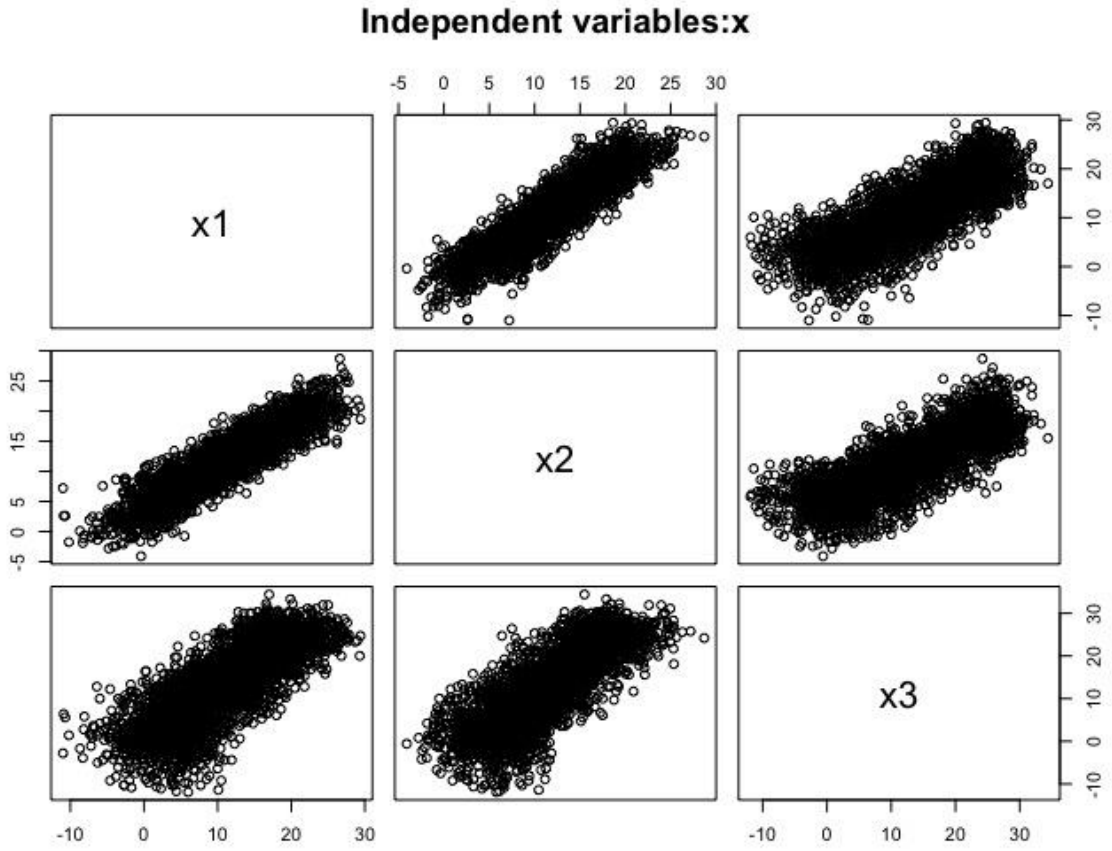
influenced by seasonal changes. A cold winter day stays a cold winter day despite of the fact that it was cold already yesterday.

The plots in the appendix give a first idea about the data we collected. Focusing on the first line in the first plot where y is plotted against all dependent variables, there is no real pattern noticeable that would imply a relation between y and any of the other variables.[2] Moreover the dots in the data crowds seem to be really random, implying that there is no relation.

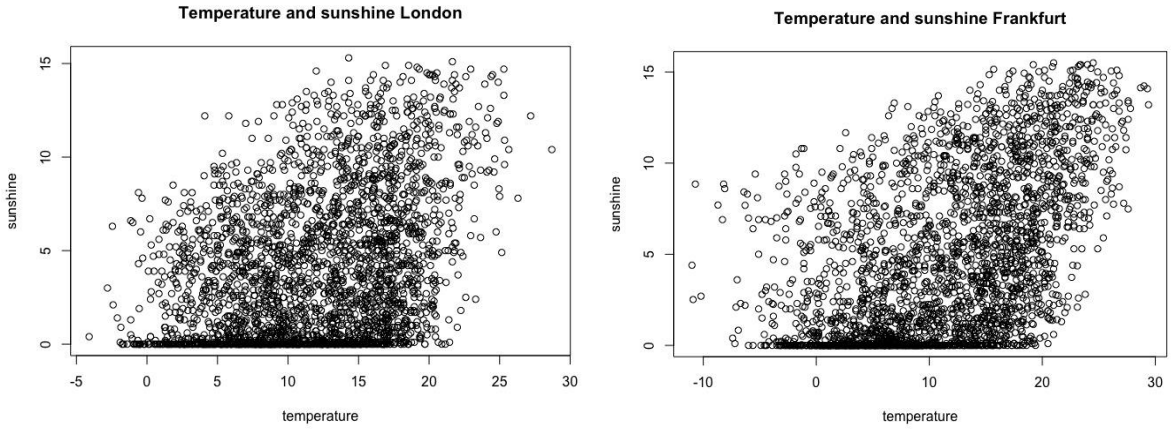


What it shows how ever is that x_1, x_2 *and* x_3 seem to have a linear relation to each other, this can also be seen in the third graph. The relation is indicated by the almost diagonal lines the single dots form in every of the single graphs. The possible correlation between weather variables can be a problem later leading to a redundant model where added weather variables do not contribute more to an explanation of the dependent variable because they do not carry "new information".

[2] plot 2 shows a zoom



Regarding the relation between average temperature and sun hours a day no clear tip can be made. The dots in both diagrams (4&5) seem to follow an upwards pattern implying a correlation but there is also a high concentration of dots around the x axis weakening this thesis. However, the charts show that correlation between the independent variables should be considered later when it comes to discussing the results of the regression analyses.



Afterwards we will investigate the connection between weather and stock prices.

3. Model

To detect wherever there is a connection between daily stock market returns and the weather we want to apply a linear regression model that departs from a single linear regression and is extended step wise to a multi linear model. During this we will use the method of least squares which is the most common used for our purpose.

We do not only use a variety of different weather variables such as daily average temperature or sunshine hours a day, but we also consider different weather in different cities, to find those weather variables that actually have an impact on stock returns. We expect that higher stock returns in a day will be related to a high temperature or to a high level of sunshine that day. As weather variables we use the average temperature and the sunshine hours in the different cities. The reason we do that is that we assume that these are the factors that influence the mood of an investor the most.

To prove this expectation, the first two regressions analyses we run will be based on the temperature and the sun hours in Frankfurt am Main. The two analyses will be performed independent from each other to perform afterwards a multi regression where both variables are considered to explain daily stock changes together. We choose Frankfurt am Main as starting point because it is the "home" of the DAX and many investors do their trading there. Even though a study of Ernst & Young (2015) (EY) shows that the composition of shareholders of companies, that are included in the DAX index, has changed between 2005 and 2014, Frankfurt am Main remains as an important harbor for German investors. The study shows in addition, that the amount of shares hold by German investors decreased from 47 to 34 percent, while the amount of shares hold by foreign investors increased from 45 percent in 2005 to 50 percent in 2014.[3] Therefore we felt the need to include weather effects from other cities to model the impact between weather, - investors' mood and stock price changes. In particular, we had to identify where the investors, that are invested in the DAX sit around the world to find a connection between their mood affected by weather at their location where they do their trading at the daily stock return in Germany. To identify every investor and his location to get a data set of the weather from that exact location to investigate the impact on the German stock changes would be nearly impossible. The EY study split the "Non-German" investors up and showed that 27% in 2014 of the German stocks included in the DAX index

[3] Not every shareholder's location could be identified

were held by investors inside the EU and 21% were held by North American investors in 2014.

Therefore, we decided to choose weather in London and New York as proxies for that, to simplify our model and in order to not have to introduce a weather variable for every single city where an investor who is trading DAX index stocks is located. The New York weather is taken as representative for the weather in North America since the majority of investors are actually based in New York. London and Frankfurt am Main together represent two of the biggest trading places in Europe, change in weather and mood at either place should affect prices of shares traded at either location including DAX stocks.

The argumentation above results in an expansion of our model: we take the temperature in all three cities into account to explain changes in y. Afterwards we are going even a step further and combine both. And go up to five independent variables in our multi regression model.

In the following the simple and the multi linear regression are shown as mathematical models. y_i will represent the daily change in stockprices in percent at day i and will be the dependent variable in all our models. The variables that represent the „weather" are: $x_{i1}, x_{i2}, x_{i3}, s_{i1}, s_{i2}$. x_{ij} stands for the temperature at day i in city 1(Frankfurt am Main), 2(London), 3(New York). s_{ij} represents the daily sunshine hours in either Frankfurt or London on day i.

These are the independent variables that are used to try to explain y. i in s_{ij} does not include New York as index since we do not have sunshine data from there.

The model we use to estimate the coefficients of the independent variable based on our data set is formulated as follows:

$$(1) \qquad y_i = d_0 + d_{x_{i1}} * x_{i1} + \varepsilon_i$$

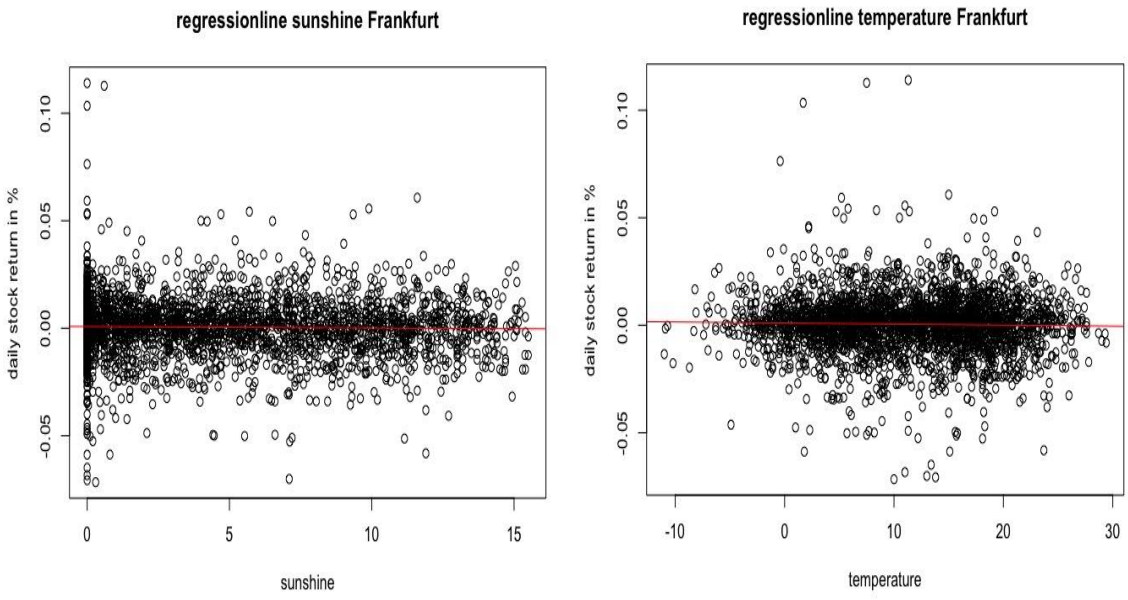
Here d_0 is the intercepts and d_1 the slope of the independent variable x_{i1} (Temperature in Frankfurt at day i). ε_i is a disturbance variable that is normal contributed with an expected value of 0 and variance greater 0. Furthermore the ε_i terms are independent from each other. To find the optimal $d_0 \; and \; d_1$ values that determine our regression line we aim to minimize ε_i for all i. As we expect that the daily change depends highly on the daily temperature or sun hours the standardized regression coefficient (B) of each independent variable should be close to 1, implying a strong influence.

This single linear regression model will be extended to a multi regression model where we add to equation (1) more independent variables in the form of x_{ij} or s_{ij} with the corresponding $d_{x_{ij}}$ or $d_{s_{ij}}$ where j is the set of cities. After we got values for the intercept and the regression coefficients we will have a look at further figures that can help us to conclude if the applied model is valid to explain the coherences or not.

4. Findings

Our findings do not indicate an influence between any of the "weather variables" and change in stock prices. In particular: the more we expand the model by including more and more independent variables, the less it explains the change in y and the less reliable it becomes. Table 1 in the appendix shows the coefficients for all independent variables in different models we ran as well as adjusted R2 values and p values for every model.

The first model we ran and where x1 was the only independent variable gives us the smallest p-value of all our findings indicating that the value of the coefficient is not only due to a random sample but could be actually significant. Thus the p-value is with 0.1512 still so high that there is no significance to a level of a=5% or less for our calculated coefficient. The adjusted R2 value shows furthermore that even if the coefficient would be significant, our model would only explain 0.03796% of the total variance that occurs. This in combination with the very close to 0 regression coefficient implies a very low linear correlation. This can also be seen in plot 6 in the appendix where the red line, which is the regression line going through the data cloud, is far away from being a diagonal line.



Our solution suggests that, if the temperature rises one day in one degree Celsius the stock price in average will move by: $-5.071e-05\%$ a day. This is a negative amount but it is so small that it would not be useful to use the temperature as indicator for stock changes that day. As mentioned before the correlation is also highly unsure and there are 1-0.0003796 percent of variance that have to be explained through other influences on stock changes than though a rise in temperature in Frankfurt am Main. In conclusion it can be said, that the temperature in Frankfurt am Main at one day is not useful to predict changes in stock price. We find similar things when we only look at the sun hours a day in Frankfurt. The regression coefficient is also very close to zero and the corresponding p value is even higher, indicating that d_{s_2} would be significant at an α level greater than 23,12 %. Since in common literature it is widely accepted that the highest acceptable alpha level is 5%, this finding is not significant either. The sun hours in Frankfurt explain less of the total variance in stock change than the temperature in Frankfurt, making it in total an even worth measure to estimate stock price changes.

Going on with our analyses and expanding the model to a multi regression model, we find that our findings get more and more insignificant, indicated by the rising p-value. Furthermore the adjusted r value does not rise by a fair amount when we include more independent variables. In fact it is even decreasing. This indicates that we do not really add a new possibility to explain y when we add new independent variables. Meaning that our multi regression model could be redundant in terms of independent variables.

5. Reasons for our findings and possible explanations

As different paper show that sunlight or temperature can affect the mood, we discovered that in our research, there is no correlation between the weather and the change in the DAX index.

But why do our results differ? Therefore, we look at our model and the results first. Than we take a look at high frequency trading in combination with today's technology advantages and afterwards we conclude with the psychological aspect.

5.1 Weaknesses of our model

At the beginning, we should analyse our model and see what did not exactly work as expected or should be done differently. One major aspect is that we do not have complete data for all the points we wanted to look at. Since the sun hours are missing for New York, we could not analyse these and compare them to the other locations. However, we were able to compare all average temperatures, for which we were able to find data for all three locations.

Unfortunately, the missing data makes our research incomplete, a fact we were not expecting. However, the model was still usable and we got results with the data we received.

The goal for the model was to use the different independent weather variables and add them, to expand our model to try to explain more and more of the changes in the daily stock prices. However as mentioned before the expansion did not add any value to our model, in the contrary it even weakened it. This is indicated by the rising adjusted p-value during expanding the model. As concluded before this is a hint to a redundant model.

To detect wherever our model was redundant we performed a correlation analyses between our independent variables. The closer the correlation output factor is to one, the bigger is the correlation between the factors. The figure outcome can be seen in the appendix (Table 2: correlation). The analysis shows that especially the average temperature variables are highly correlated. But there is also a correlation between the two different kinds of independent variables: temperature and sunshine hours in general. This correlation causes a problem in our model. One added independent variable does not really add any value to explaining stock price changes in Germany due to the fact that the already included independent variables carry almost the same information.

Another factor, which should be mentioned, is the cities we chose. As discussed in the EY study 2014, 35% of the money invested into the DAX comes from Germany. However, 27% of the investors are from other European states and 21% are located in North America. Since we do not know who is investing or where they have their headquarters, we just have to make an assumption and use one major city, known for trading, in order to use it in combination with the weather changes. Therefore, it might be too broad to say that all of the investors from North America are sitting in New York or all of the investors from other European states are situated in London. Additionally, nearly 17% of the investors could either not be able located due to missing data or belong to the section “rest of the world”. That means we could not use these types of investors in our research, because we were not able to allocate them to a city and therefore no correlation with the weather could be made. We decided to just leave them out of our analysis, which shows another weakness of our paper, since we excluded nearly one-fifth of the investors.

Unfortunately, we were not able to change this perspective and could only work with this assumption. Further research can focus on a more diverse allocation of chosen cities.

However, compared to the other research papers mentioned above, we have different results, which cannot be compared with each other. There are several reasons for this. For example, we use other weather parameter as Hirshleifer and Shumway (2003) or Saunders (1993). Both use the cloudiness as a parameter in their research. In our model the primary parameters are the hours of sunlight per day and the average temperature per day. This implies another difference in the results. Therefore, sunshine and temperatures have less to almost no significant influence on the mood of investors. Therefore, compared to the weather parameter cloudiness, which has an influence, the hours of sunshine per day and the average temperature have no influence on investment decisions.

5.2 Change in technology and high frequency trading

The world is in rapid changes. In the last decades, globalization has influenced our society and everyday life. This influence also occurred in trading shares on the stock market, which led to a more often use of technology and algorithms. Resulting, high frequency trading (HFT) became more common and "over the past years, high-frequency trading has progressively gained a foothold in financial markets" (Chlistalla, M. 2011). HFT aims to have only short-term positions and usually do not carry big positions into the next business day (Chlistalla, M. 2011). In addition, big numbers of shares, usually consisting out of small size, are traded with a high speed into the market. "Empirical evidence reveals that the average U.S. stock is held for 22 seconds" (Chlistalla, M. 2011). Carried out by high-speed computers running a program to detect trading opportunities, the speed gives the trades an advantage compared to normal trading. However, looking at our research, we can say that HFT is definitely not influenced by weather changes, neither temperatures nor sun hours. This fact could be one reason for the differences of our results compared to other research papers. Therefore, the data we used is more contemporary, which means we have to adapt our study to the current situation, with for example HFT.

Another fact of technology is that we live more comfortable than the years before, meaning more air conditioning and heating is used. For example, no one on Wall Street has to sweat through a hot summer anymore. Human beings try to keep their working atmosphere as suitable as possible, which lowers the effect of extreme weather conditions on the mood itself.

5.3 Effect of mood on decisions

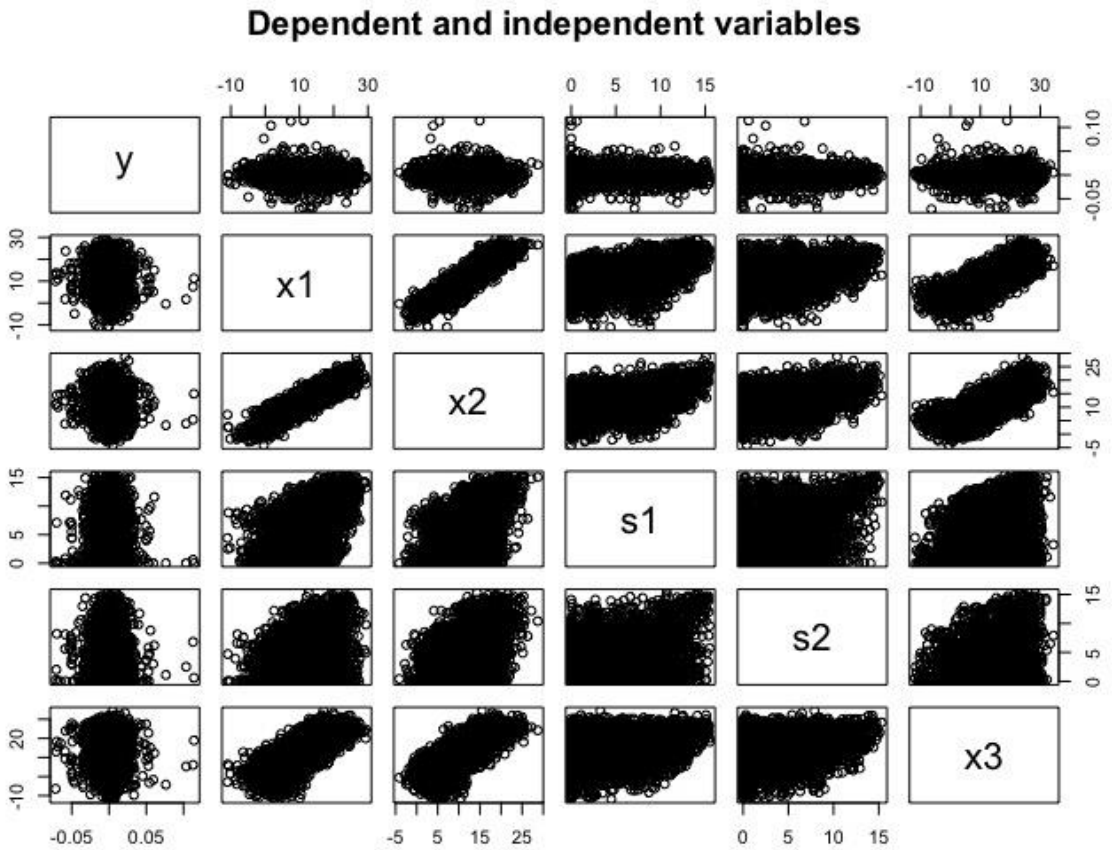
There are different researches whether weather has influence on the mood of persons or not. In our research we find out that the temperatures and also the hours of sunlight do not have an influence on the investment decision of persons. Therefore, we can say that the DAX index is

not influenced by these factors either. A possible reason for that can be found in human psychology. It is highly unlikely that only weather affects the mood of a person. There are for sure other factors that determine if a person is in a general good mood or bad mood. In addition to that it is also highly questionable that stock prices only depend on the mood of the investor. No investor decides whether he buys or sells stock only on a feeling in his stomach. Moreover, there are other relevant attributes he takes into account, especially hard figures like profit or loss and possible return on investment. However, our model does not include those factors.

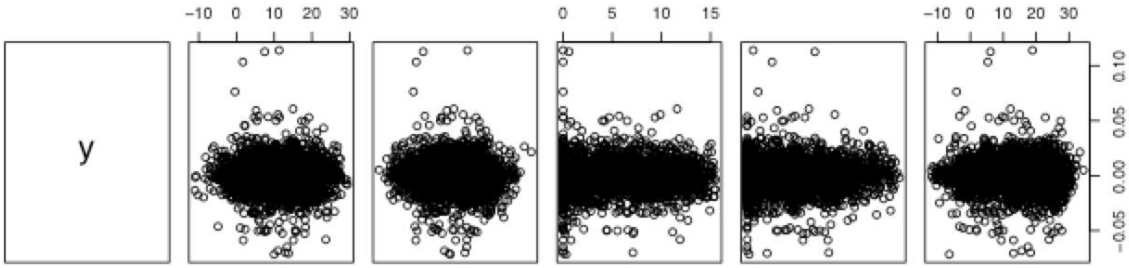
Conclusion

Over the last couple of years many scientists examined wherever there is a connection between weather, mood and daily stock price returns. They looked at many different markets and used different analyses techniques, some found a correlation and some did not. We took on this subject and looked at the German stock index DAX and tried to explain daily stock changes through average temperature and/or sunshine hours a day. Our (multi) regression model did not find any correlation whatsoever. The more we tried to include the weather, the weaker our results got. One reason might possibly be rise in automatic computer trading which is not dependent on the weather at all and takes only hard factors into account. Over all there are many more factors that not only influence mood of humans but also determine stock prices than only the weather.

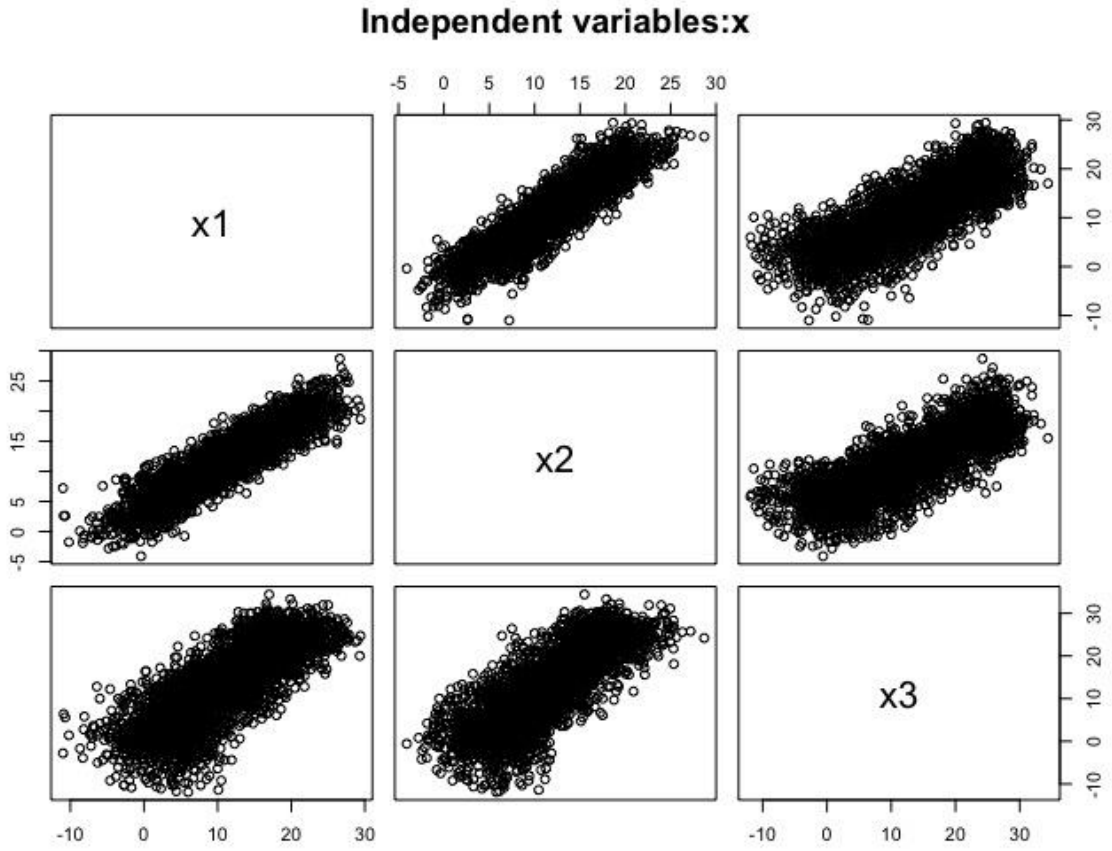
Appendix



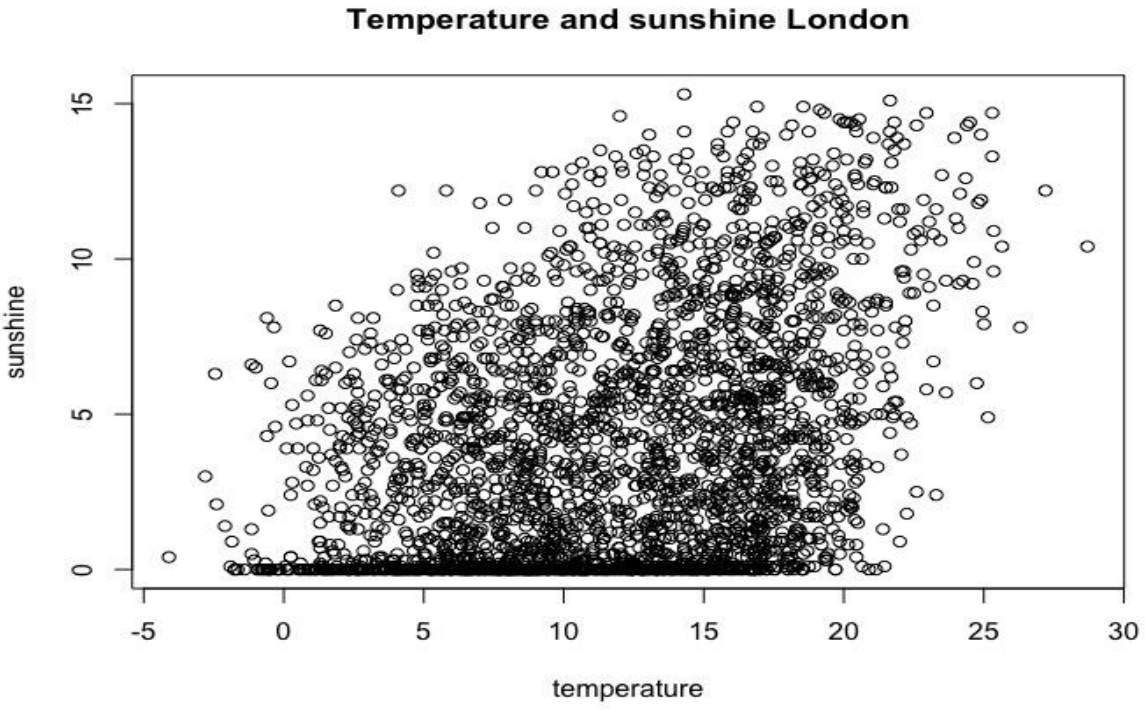
Plot 1: dependent and independent variables plotted against each other.



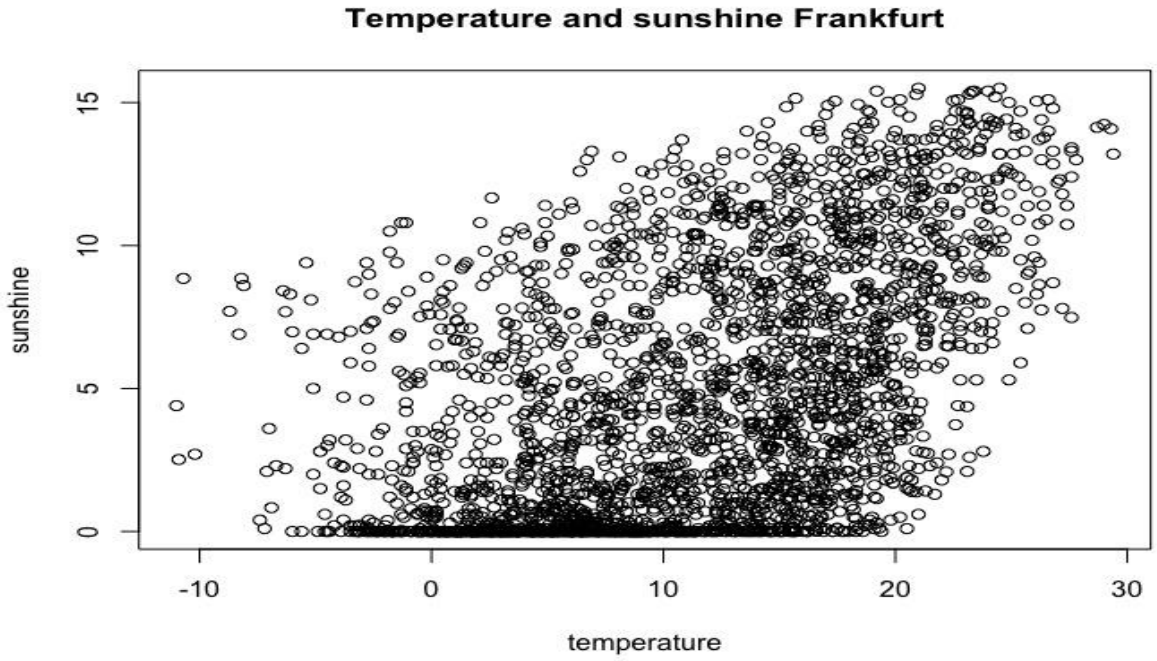
Plot 2: zoom of the first row of plot 1.



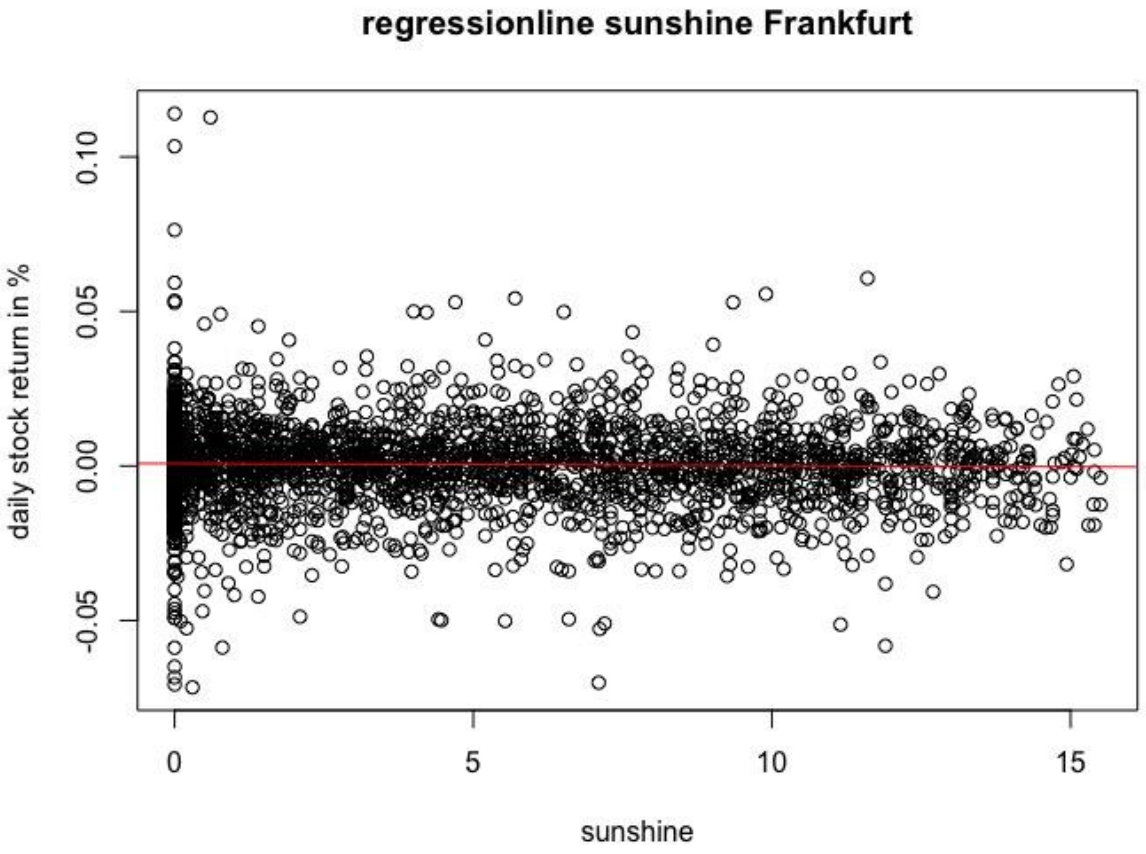
Plot 3: independent x variables plotted against each other



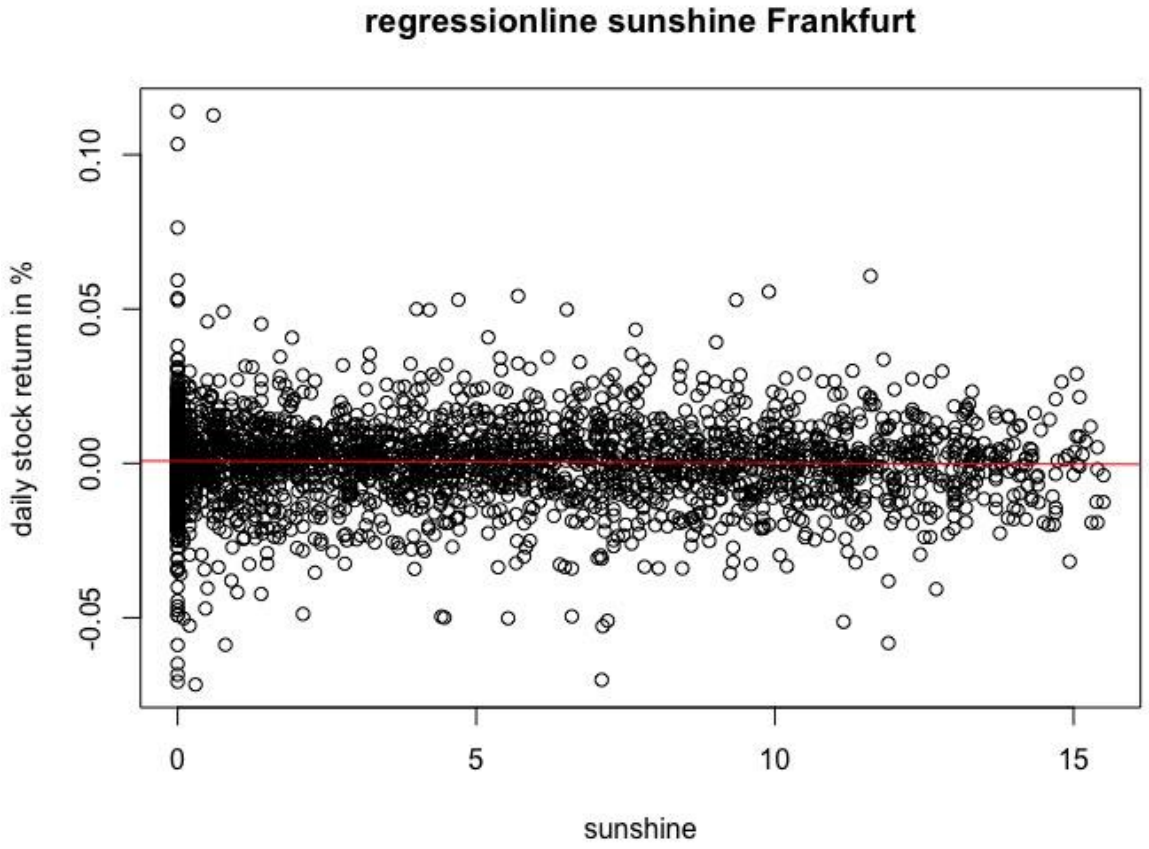
Plot 4: temperature and sunshine in London plotted against each other.



Plot 5: temperature and sunshine in Frankfurt am Main plotted against each other.



Plot 6: the regressionline plotted with the temperature in Frankfurt am Main as only independent variable.



Plot 7: the regressionline plotted with the sunshine in Frankfurt am Main as only independent variable.

Included independent Variables	P-value	Adjusted R2	coefficients
x_{i1}	0.1512	0.0003796	$d_{x_1} = -5.071e-05$
s_{i1}	0.2313	0.0001551	$d_{s_1} = -7.201e-05$
x_{i1}, x_{i2}, x_{i3}	0.4126	-4.735e-05	$d_{x_1} = 8.439e-06$ $d_{x_2} = -1.049e-04$ $d_{x_3} = 1.227e-05$
s_{i1}, s_{i2}	0.433	-0.0001165	$d_{s_1} = -8.473e-05$ $d_{s_2} = 4.108e-0.5$
x_{i1}, x_{i2}, x_{i3} s_{i1}, s_{i2}	0.5982	-0.0004771	$d_{x_1} = 1.222e-05$ $d_{x_2} = -1.005e-04$ $d_{x_3} = 7.31e-06$ $d_{s_1} = -4.591e-05$ $d_{s_2} = -6.311e-05$

Table 1: table of results

	x1	x2	x3	s1	s2
x1	1	0,906788779	0,791614607	0,517301803	0,366483269
x2	0,906788779	1	0,797566872	0,494389087	0,37056262
x3	0,791614607	0,797566872	1	0,407659117	0,339321935
s1	0,517301803	0,494389087	0,407659117	1	0,395913245
s2	0,366483269	0,37056262	0,339321935	0,395913245	1

Table 2: correlation between the independent variables.

References

Chlistalla, M. (2011) High-frequency trading. Better than its reputation?. Deutsche Bank Research.

Deutscher Wetterdienst (2016) http://www.dwd.de. Retrieved 12 4, 2016, from ftp://ftp-cdc.dwd.de/pub/CDC/observations_germany/climate/daily/kl/.

Ernst & Young GmbH (2014) Wem gehört der DAX? Analyse der Aktionärsstruktur der DAX-Unternehmen. Ernst & Young GmbH Wirtschaftsprüfungsgesellschaft.

Frühwirth, M. & Sögner (2015) Weather and SAD related mood effects on the financial market. The Quarterly Review of Economics and Finance, pp. 11-31.

Hirschleifer, D. & Shumway, T. (2003) Good Day Sunshine: Stock Returns and the Weather. The Journal of Finance, Vol. 58, No. 3, pp. 1009-1032.

Howarth, E. and Hoffman, M. (1984) A multidimensional approach to the relationship between mood and weather. British Journal of Psychology, pp. 15-23.

Kaustia, M. and Rantapuska, E. (2015) Does mood affect trading behavior?. Journal of Financial Markets, pp. 1-26.

Met Office UK (2016) http://www.metoffice.gov.uk. Retrieved 12 4, 2016.

National Climatic Data Center (NOAA)(2016) https://www.ncdc.noaa.gov. Retrieved 12 4, 2016, from https://www.ncdc.noaa.gov/ghcn/comparative-climatic-data.

Saunders, Edward M., Jr. (1993) Stock prices and Wall Street weather. The American Economic Review: American Economic Association, Vol. 83, no.5, pp. 1337-1345.

Spasova, Z. (2012) The effect of weather and its changes on emotional state – Individual characteristics that make us vulnerable. Advances in Science & Research.

Symeonidis, L., Daskalakis, G. and Markellos, R. (2010) Does the weather affect stock market volatility?. Finance Research Letters, pp.214-223.