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Impact of Weather on the Stock Market Returns of Different Industries in Germany

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Abstract

Weather affects people's mood, according to psychological studies. For example, low temperature can cause aggression, whereas high temperature can induce apathy. Therefore, it may be possible that weather-influenced mood, driven by mood's impact on decision-making, exerts an influence on investment decisions and risk-taking behaviour. Thereby, it might also impact stock market returns. I examine market returns of nine industries in Germany. Empirical results illustrate two findings. First, a statistically significant, negative correlation between market returns and temperature, second, a different effect of weather on industrial sectors is identified. A significant correlation can be found for six out of nine sectors.

Keywords: Stock markets; investor behaviour; weather effect; market returns; decision-making.

1. Introduction

The impact of climate change has become noticeable on a global level, and Germany has experienced more extreme weather phenomena during the last years. According to the German weather service (Deutscher Wetterdienst (DWD)), the summer of 2018 marks the second hottest summer on record since 1881 (Imbery et al., 2018). Further, weather and climate implications on companies' earnings are increasingly discussed on executive earnings calls, and rating agencies have started to focus on weather implications on companies' economic performance (Williams et al., 2018).

Investigating weather implications on the economy is a relevant field of study that is already supported by extensive research. For example, weather has been linked to stock market performance. The underlying reason for connecting these fields is that research has found evidence that weather conditions affect mood and spawn mood misattribution. A change in emotional state can trigger an alternated risk assessment and in turn a revised investment behaviour. This can ultimately lead to changes in stock market returns. Based on this finding, my study analyses if a relationship between weather and stock market returns exists.

Several researchers have carried out studies in the field of weather implications on psychology. Howarth and Hoffman (1984) observed that human performance is positively correlated with sunshine, and aggressiveness increases with low temperature. On the opposite, high temperatures have been associated with apathy (Cao and Wei, 2005). On sunny days, people are inclined to rate their life satisfaction higher than on cloudy days (Schwarz, 1990). People's mood is linked to their decision-making (Schwarz, 1990). Thus, it is also a component of their investment decisions.

Turning to empirical research, Saunders (1993) was among the first who linked weather to investors' behaviour. He reported a negative correlation between NYSE index returns and the degree of cloudiness. His results support the conjecture that investors are overoptimistic on sunny days and more pessimistic on cloudy days. Further evidence for the negative relation between cloud cover and stock market returns were given by Hirshleifer and Shumway (2003). In 18 out of 26 cities, a negative relationship could be reported. Other research produced evidence for a negative correlation between stock returns and temperature (Cao and Wei, 2002; Chang et al., 2006; Kang et al., 2010).

Moreover, the seasonal affective disorder (SAD) has an impact on stock returns. Affected people show depressive symptoms during winter, and consequently, stock market returns are lower during this time of the year. Kamstra et al. (2003) call this effect winter blues.

1.1. Relevance

My paper expands on the existing research by examining the probable linkage between stock returns and weather variables temperature and precipitation with a focus on Germany and differentiating between sectors. The former is advocated to be among the most essential meteorological variables to alter people's mood. The latter is only included in a minor

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part of literature yet and therefore will be further explored. In particular, my analysis examines the impact of temperature and precipitation on the stock market return of different industries in Germany. Hence, I will contribute to a yet unexplored field by differentiating stock market return behaviour between sectors. Hitherto, only stock market indices on a global scale or across industries have been analysed. While most research focuses on adjusting the independent variable set containing weather data, refinements of the dependent variable in the form of separation of industries are somewhat limited.

Weather does not only impact mood and decision-making but also it has economic implications on companies' economic efficiency. Therefore, my study expands upon the relationship between weather and stock market returns by also incorporating economic implications. It is evident that the climate and weather implications on the economy might vary across sectors. This is because integral parts of the supply chain or the use of the finished product depend to ranging degrees on environmental circumstances as the weather. Temperature, for example, might influence the demand for some products. Especially in the Retail and Utilities industry, demand may increase during periods of lower temperatures, whereas the economic performance of other companies is harmed when temperatures are high. These effects might also be present in the opposite direction because high and low temperatures can both be beneficial and unfavourable, depending on the industry. I also conjecture that precipitation might carry weight in the determination of stock market returns.

Germany as the country of research has only been investigated once on a national level by Krämer and Runde (1997). Their study concluded that no systematic relationship exists for the German stock market returns and weather variables. The rejection of the null hypothesis is rather determined by the manner the hypothesis is phrased. My study will elucidate whether those outcomes can be confined and can be replicated for a later period of time.

As psychological literature has outlined, weather influences people's mood and behaviour. Consequently, the risk assessment and investment decisions of traders could be altered. If this holds, trader's evaluation of companies might be over- or under-optimistic depending on the weather. Likewise, hot temperatures might induce a change in the evaluation of some industries. Another approach could be that changes in weather influence the mood of traders only for some particular industries. Certain sector-returns might not be affected by the weather at all. The inference seems appropriate, if one considers the impact of changing weather conditions through global warming on politics and industries today. By dividing into industry groups, it is finally possible to assess whether all company returns are affected by the weather or if this phenomenon is limited to specific sectors.

From a psychological point of view, potential findings could be used for weather-based trading strategies. From an economic standpoint, a sector might be attractive for stock trading, if its market returns are influenced by weather. Industries that are not correlated to weather variables might be more valuable for a buy and hold strategy. In general, the findings could not only be interesting for traders, but also be interesting for investors, and financial managers.

1.2. Structure

The remaining part of this paper is structured as follows. Previous qualitative and quantitative work is discussed in section two. Section three outlines the methodology and section four describes the data set which was collected for both weather and stock market returns, including descriptive statistics. Section five outlines the underlying hypotheses and leads to the central part of this paper. A detailed analysis of the relationship of weather with stock market returns is given in section six by using both a bin-test and an EGARCH model. Section seven will discuss my findings. Section eight will provide a further outlook and highlights the potential limitation of my work; afterwards, section nine concludes.

2. Literature review

Thorough research on the topic has made it evident that behavioural finance uses a systematic approach for the analysis of the potential impact of weather on an investors' psychology. The first part, thus, will elaborate on the effects of weather on human beings' mood. The second part will discuss the impact of mood on decision-making, and the third part presents research that links weather conditions with investment behaviour and consequently stock markets. The underlying process is illustrated in Figure 1.

2.1. Weather and mood

One-third of humans respond sensitively to weather, which is characterised by changes in mood and human well-being (Kals, 1982). More precisely, weather can provoke compound physical and psychological responses, including changes in performance, aggressive behaviour, and interpersonal interactions (Lu and Chou, 2012; Shu and Hung, 2009). The phenomenon has been discussed in a large body of literature, where the weather has been linked with human behaviour (Hirshleifer and Shumway, 2003; Howarth and Hoffman, 1984; Parsons, 2001; Pilcher et al., 2002; Rind, 1996; Watson, 2000). In current research, temperature is the most prominent influencing factor for people's mood. Especially, low temperature can fortify aggressive behaviour and discomfort. This effect also holds for high temperatures where apathy and hysteria are caused in addition to aggression (Cao and Wei, 2005; Pilcher et al., 2002). Extreme temperatures can also induce a decline in task performance (Pilcher et al., 2002), as well as a greater willingness to offer help to other people (Cunningham, 1979). Sunshine, on the opposite, can lead to higher satisfaction on sunny days in comparison to cloudy days, and consequently can enhance people's optimism (Howarth and Hoffman, 1984). Moreover, sunshine has been proven to influence the amount of tipping, as confirmed by Rind (1996). On the contrary, lack

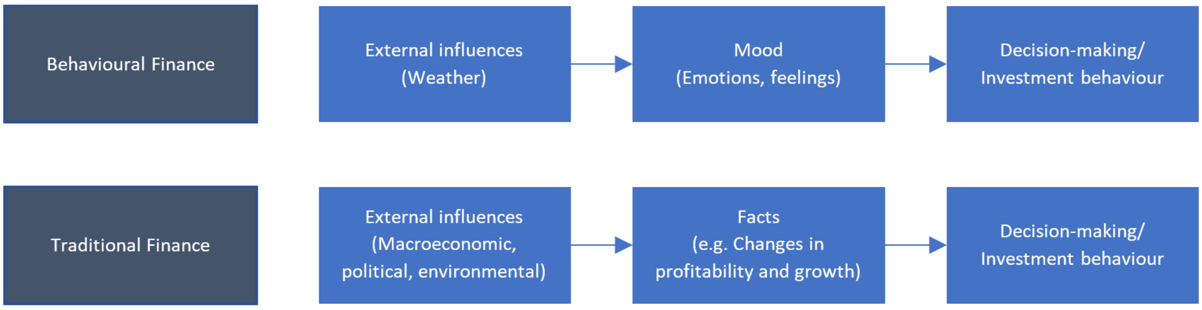

Figure 1: Self-created process model of the impact of external influences on mood and decision-making

of sunshine was noted to cause depression (Eagles, 1994) and suicide (Tietjen and Kripke, 1994). Sariannidis et al. (2016) claim that wind is directly linked with investors' feeling of safety. With higher wind speed, air pollution is diluted, and therefore particles of dirt accumulate less. Humidity is an indicator that can lower human comfort and simultaneously lead to more aggressive behaviour (Cao and Wei, 2005). Since ancient times, the impact of the moon, especially the full moon, has been associated with changes in human feelings. Research has confirmed a shift in the behaviour of people: higher occurrence of somnambulism, crime, and mental disorders (Zheng et al., 2001).

2.2. Mood and decision-making

As weather can affect mood in various ways, this part will review psychological evidence that a change in mood, feelings, or emotions can influence decision-making. Among scholars, no consensus on the definition of the three terms exists, and the words are frequently used interchangeably.

Schwarz was among the first to identify that mood influences decision-making (Schwarz, 1990). He constitutes that mood can have an impact on the judgement of the information capabilities of a person. Further, a good mood can induce a more positive appraisal of life satisfaction (Wright and Bower, 1992) and prospects (Hirshleifer and Shumway, 2003). Also, a more intense utilisation of simplifying heuristics by individuals was identified in the respective research (Bless et al., 1996). Consequently, individuals base their judgement on stereotypes and are more likely to identify a deviation of available information from pre-existing knowledge. Other research has found that positive mood can lead to a higher receptiveness to weak arguments (Mackie and Worth, 1991), while it can enhance problem-solving abilities and creativity (Isen, 2002). According to Schwarz (1990), not only mood but also feelings are linked to decision-making. He further claims that through misattribution, emotions are connected to a false origin and consequently, induce incorrect judgements. Thus, the capability to process information is hindered and especially investors falsely respond to irrelevant information in a state of happiness. Also, visceral factors exert an influence on human beings' preferences (Hirshleifer and Shumway, 2003). Summarising, mood affects judgement, choices, and decision-making.

2.3. Stock markets and weather

Behavioural Finance is a field of research that has as its central premise the investment decision of individuals. In contrast to Traditional Finance, it is based on the theory that decision-making by individuals is not always rational but based on the impact of emotions and mood. Kahneman and Tversky are considered essential contributors to Behavioural Finance, promoting the non-existence of a "homo economicus". Instead, cognitive biases and heuristics guide an individual's behaviour and lead to irrational decisions. Consequently, arguments of the field of Behavioural Finance support the view that investment decisions are linked to people's mood. As summarised in section 2.1, weather conditions can influence mood and can cause for instance misattribution. They might also lead to changes in risk assessment and consequently altered tendencies in investment activities. Pleasant weather can lead to more communication, which expands information transfer, thereby encouraging investment activity (Symeonidis et al., 2010). Favourable weather conditions can also induce good mood. Investors transfer this positive state and evaluate economic prospects more optimistic (Shu, 2010) as they underestimate risk and overestimate the probability of success (Wright and Bower, 1992). As a result, stock market returns might be influenced by weather-induced effects. Existing research has not only linked mood to weather but also has investigated potential relationships between stock market returns and various meteorological variables. There is both literature supporting and rejecting the relationship between weather and stock returns.

Temperature (Cao and Wei, 2005; Chang et al., 2008; Floros, 2008; Keef and Roush, 2002), number of sunshine hours (Pardo and Valor, 2003; Shu and Hung, 2009), cloud cover (Hirshleifer and Shumway, 2003; Saunders, 1993) and air humidity levels (Chang et al., 2006; Pardo and Valor, 2003; Sariannidis et al., 2016) are, among others, the standard variables to measure weather's influence on stock market returns. Also, other nature-related variables such as the daylight-savings time change (Kamstra et al., 2000), the length of the night (Kamstra et al., 2003), and the lunar phases of the moon (Dichev and Janes, 2001; Zheng et al., 2001), have been used as weather proxies that might influence an investor's mood.

2.3.1. Evidence of the weather and stock market relationship

Saunders (1993) was among the first researchers to connect weather variables with stock market returns. By using daily returns of the Dow Jones Industrial Average from 1927 to 1989, as well as equal- and value-weighted daily percentage changes in the NYSE/AMEX index from 1962 to 1989, he identified a significant negative correlation between the percentage of cloud cover and stock returns. This effect is robust with respect to various market anomalies, including the Monday and January effect. Consequently, Saunders conjectures that the mood of investors is overoptimistic on sunny days.

Further evidence for this sunshine effect has been given by Hirshleifer and Shumway (2003) who access the level of cloudiness in 26 countries from 1982 to 1997. An OLS regression model and a logit model both indicate that cloudiness exhibits a strong negative effect on returns in the majority of countries. The results remain stable after controlling for seasonality. This finding emphasises the conjecture that overcast sky reinforces a downbeat mood. Therefore, the researchers raise the question of whether a trading strategy based on a sunshine effect exists.

The research of Dowling and Lucey (2005) emphasises the relationship between stock market returns and rain and concludes that both variables are negatively correlated. This outcome is in line with the study of Saunders (1993), as "85% of rain occurs on days with 100% cloud cover" (Dowling and Lucey, 2005, p. 18).

A vast base of stock-market-focused literature uses temperature as a weather proxy. For most of the studies, a negative relationship has been found between temperature and stock market returns: The higher the temperature, the smaller the return.

For example, in an investigation of eight stock exchanges, Cao and Wei (2002, 2005) have found a negative correlation between temperature and market returns.

Negative correlation of temperature, sunshine, and humidity on the returns of the Shanghai stock market has been documented (Kang et al., 2010). Similar results were identified by Yoon and Kang (2009) for Korean stock returns. Here, for the whole period of 1990 to 2006, high temperature and humidity negatively influenced stock returns, while high cloudiness and low humidity led to positive stock returns. For the Taiwan stock exchange, temperature and cloud cover have a significant effect while humidity is not significantly correlated (Chang et al., 2006).

Keef and Roush (2007, 2002) have studied both the Australian and the New Zealand Stock Exchange, deriving the conclusion that temperature negatively affects returns. Whereas wind speed and cloud cover do not have a significant impact on the Australian stock returns, wind is indeed significant for returns in New Zealand. A further study of the researchers from Keef and Roush (2005) does indicate a negative correlation between New Zealand stock prices and wind, as well as a positive effect of sunshine on bank bills.

Kamstra et al. (2000) draw attention to the effect of sleep desynchronosis, an interruption in sleep patterns, induced through daylight saving time changes on stock returns. Further, the seasonal affective disorder, caused by fewer daily sunshine hours, has a significant impact on stock returns in several countries (Hirshleifer and Shumway, 2003). The researchers provide evidence that longer nights correlate with lower stock returns.

Europe has also served as a ground for studies in the field of weather impact on stock exchanges (Floros, 2011, 2008; Sariannidis et al., 2016). Hereby, negative relationships between weather variables and stock returns were again identified (Shu and Hung, 2009).

2.3.2. Evidence against the weather and stock market relationship

Contradicting with previously discussed findings is the research by Trombley (1997) who replicated Saunders results without finding any significant correlations. Thus, he states that "[Saunders's] choice is the only comparison during this period that would produce a statistically significant test statistic and does not consider that the returns on the zero percent days are inconsistent with the existence of a weather effect (p.13)."

Replication of Saunders result with German data has also supported Trombley's view (Krämer and Runde, 1997). Further, the researchers Krämer and Runde claim, that the significance of results, and a systematic relationship between weather and stock returns, does mostly depend on the phrasing of the null hypothesis and the variables. Loughran and Schultz (2004) receive little evidence in their analysis of the effect of cloudiness in the location of the company's headquarter on the returns of NASDAQ stocks.

Moreover, wind speed is no indicator for returns, as proven by Shu and Hung (2009) who analysed 18 European countries from 1994 to 2004.

Extant work by Zhu and Goetzmann (2003), who focused on data of individual traders during the period 1992 to 1996, further proved that not the weather, but the bid-ask spread led to investors' propensity to buy or sell. These findings are consistent with Pardo and Valor (2003) who provide evidence that humidity is not correlated with the Madrid Stock Exchange. This serves as an example of rational human behaviour. Lu and Chou (2012) also derive that the relationship between weather and stock market returns is insignificant. However, they identified that humidity and wind exert a positive effect on the volatility of stock indices, as shown with the Shanghai Stock Exchange.

In contrast to the research of Dichev and Janes (2001), who identified a strong effect of the lunar cycle on stock returns that is consistent over the last 100 years and for the majority of the 24 countries analysed, Rotton and Rosenberg (1984) have gathered evidence that shows no significant effect of the lunar phases on the Dow Jones Index prices.

Taken together, the relationship between weather and stock returns is controversial (Floros, 2011; Sariannidis et al., 2016) and research results differ. Locations, data, and the time horizon used are distinct among extant research and cannot lead to a generalised conclusion. However, it can be said that there is a significant body of literature that has provided evidence on an existing relationship between weather-related variables and stock market returns. If that holds, the marginal investor's behaviour is dependent on the weather, the season of the year, the phases of the moon, the daylight-savings time, and the length of the night. According to Zhu and Goetzmann (2003), the market is therefore not efficient, and this leaves opportunities to exploit its inefficiency. Investors can benefit from the awareness of the impact of their mood, as Hirshleifer and Shumway (2003) Suggest. Nevertheless, they also claim that mood is influenced not only by weather but also by other factors and biases.

The existence of the weather's influence on stock returns cannot be denied and raises the question on whether this effect is limited to countries and the industry as a whole or whether sectors are affected differently by weather variables. Having a profound body of literature as a base, the material will be used as a guide to analyse a yet underexplored field of research.

3. Methodology

The purpose of this paper is to gain valuable insight into the impact of weather on stock market returns in different industries in Germany. Literature has made use of a variety of analysis tools to investigate the relationship between market returns and weather. For this purpose, weather variable data and industry return data have been collected. The following paragraphs will describe the methodology of my analysis which will be grouped into two types of tests. Afterwards, the data collection shall be discussed.

3.1. Bin test

The first analysis, following Saunders (1993), is called Bin test based on Cao and Wei (2005). For this, I will use both industry index returns and the meteorological variable temperature. It will enable the identification of relationships between temperature and returns by matching temperature and return data, grouping it into bins, and calculating z-scores to evaluate the statistical difference between the bins. However, this test cannot identify specific correlations and lacks the ability to control for known stock return anomalies. The underlying methodology and detailed steps will be explained in the following.

First, the daily return and respective temperature data are sorted in descending order and separated into four bins. For each group, the mean return and the frequency of positive return are calculated, and the mean returns of the first and the fourth bin, covering the lowest temperature and the highest temperature respectively, will be compared. This will allow for the evaluation of the potential significance in the difference in mean return. Another comparison will be made between the percentage of positive returns in the four bins to verify whether the return difference is caused by outliners.

In detail, first, the four bins are identified by taking the range between maximum and minimum temperature and dividing by the total number of k bins with $(k = 1, \ldots, 4)$.

$$\Delta = \left(\text{Temperature}_{\max} - \text{Temperature}_{\min}\right)/k \quad (1)$$

The bin ranges are then calculated as followed: $[\text{Temp}_{\min} + \Delta], [\text{Temp}_{\min} + 2\Delta]$ and so forth. Based on the procedure by Saunders (1993), a z-test is performed to verify whether mean return differences of bin one and four are statistically significant.

$$z\_\ \text{score}_{4,1}^{\text{mean}} = \left(\mu_4 - \mu_1\right)/\sqrt{\frac{\sigma_4^2}{n_4} + \frac{\sigma_1^2}{n_1}} \quad (2)$$

The variable μ_i describes mean return, σ_i^2 is variance of return and n_i the number of observations per bin i with ($i =$ 1, or k). A z-statistic is also performed for the percentage of positive returns per bin, to examine whether there is a significant difference between frequency of positive returns in the two extreme bins.

$$z\_\ \text{score}_{4,1}^{\text{frequence}} = \left(p_4 - p_1\right)/\sqrt{\frac{p_4\left(1-p_4\right)}{n_4} + \frac{p_1\left(1-p_1\right)}{n_1}} \quad (3)$$

In this case, p_i is the percentage of positive return for bin i ($i = 1$, or k).

3.2. EGARCH model

In financial research, the generalised autoregressive conditional heteroscedasticity (GARCH) model has been used extensively to investigate the relation between weather variables and stock market returns. The Glosten, Jagannathan, and Runkle (GJR) GARCH model has been utilised by Chang et al. (2006) and Symeonidis et al. (2010), other researchers employed the autoregressive threshold GARCH (AR-TGARCH) (1,1) model (Floros, 2011) or a simple GARCH(1,1) analysis (Kang et al., 2010). My study will make use of an exponential GARCH (EGARCH) model by Nelson (1991), and it resembles the core of my thesis.

The EGARCH model is applied because it is frequently argued that stock return shocks are asymmetric. Positive return shocks have a lower impact on volatility than negative return shocks of the same magnitude. This phenomenon is called leverage effect. Further, the model captures volatility clustering, which is typical for financial time series. The omitted parameter restriction can result in more reliable optimisations. It also makes this model robust against changes in volatility and against long-run memory effects which are a result of time-varying clusters. Besides, the EGARCH model uses the natural logarithm ln(.) which guarantees the positivity of the parameters. As a result, the EGARCH model has been often seen to be superior to other models.

The regression equation of the EGARCH model including return R, prices P, and a stochastic error term, is expressed as follows:

$$R_{t,j} = b_0 + b_1\sigma_t^2 R_{t-1,j} + b_2\sigma_t^2\,\text{Temp}_t + b_3\sigma_t^2\,\text{Prec}_t + \xi_t \quad (4)$$

$R_{t,j}$ is the daily industry return gain or loss for day t, calculated:

$$R_{t,j} = \ln\left(P_{t,j}\right) - \ln\left(P_{t-1,j}\right) \tag{5}$$

For the industry j, the subscript $j \in$ Financials, Telecommunication, Technology, Consumer Non-Cyclicals, Industrials, Healthcare, Basic Materials, Consumer Cyclicals, Utilities. $R_(t-1)$, the lagged return variable, is incorporated to account for potential nonsynchronous trading effects. Temp_t is the daily average temperature at day t, Prec_t the precipitation height in mm at day t, and ε_t is the error term at day t. The formula is consistent across all industries. The same set of variables is used for all industries.

The variable $\sigma^2_{t,j}$ is the volatility of industry j at day t of the EGARCH (p,q) model. It is an estimate of the one period ahead variance including past information that is considered relevant. For this reason, it is called conditional variance. The formula for each single industry is given by:

$$\ln\left(\sigma^2_{t,j}\right) = \alpha_0 + \sum_{l=1}^{p} \gamma_l \ln \sigma^2_{t-l,j} + \sum_{l=1}^{q} \alpha_l \left[\left|z_{t-l,j}\right| - E\left|z_{t-l,j}\right|\right] + \sum_{l=1}^{q} \xi_l z_{t-l,j} \tag{6}$$

The conditional variance consists of several parts: First, $Z_{t-l} = \frac{\varepsilon_{t-l}}{\sigma_{t-l}}$ is the standardized residual at time $t-l$ and l describes the number of lags. γ_l measures the persistence in conditional volatility irrespective of any activity in the market. Second, α_l describes the GARCH effect, which represents the magnitude effect or the symmetry effect. It gives insights into the degree to which the size of shock influences the stock market response. Third, the parameter ξ_l measures the leverage effect, which takes into consideration the asymmetry, which is an advantage of the EGARCH model. For $\xi_l < 0$, positive shocks generate less volatility than negative shocks, which is evidence for the leverage effect. For asymmetric shocks, the variable ξ_l must be non-zero ($\xi_l \neq 0$).

Returns are not normal distributions, as the JB test in section 4.3 will prove, and standardized residuals are leptokurtic. For heavier tails, the generalized error distribution (GED) is a more appropriate distribution than the t-distribution and will offer more reliable test results. The GED has the density function:

$$f\left(\mu_t, \sigma_t^2, \nu\right) = \frac{\nu}{2}\left(\Gamma\left(\frac{3}{\nu}\right)\right)^{\frac{1}{2}}\left(\Gamma\left(\frac{1}{\nu}\right)\right)^{-\frac{3}{2}}\left(\frac{1}{\sigma_t}\right) \exp\left\{-\left[\Gamma\left(\frac{3}{\nu}\right)/\Gamma\left(\frac{1}{\nu}\right)\right]^{\frac{\nu}{2}}\left|z_t\right|^{\nu}\right\} \tag{7}$$

with μ_t as the conditional mean, σ_t^2 as conditional variance, and $\Gamma(.)$ as the gamma function. The shape parameter ν indicated the degrees of freedom under the GED distribution. The GED distribution can be identical with the normal distribution for $\nu = 2$ and to the Laplace distribution for $\nu = 1$. For $1 = 2, \nu = 2$, and $\nu \to \infty$ degrees of freedom, the GED distribution converges to uniform density.

An estimation for the maximum of the log-likelihood function, which can also be considered a quasi-maximum likelihood function, is given as follows:

$$L(\theta) = \sum_{t=1}^{T} \log f\left(\mu_{t-1}, \sigma^2_{t-1}, \nu\right). \tag{8}$$

4. Data set

The dataset used will be described in the following paragraphs. For my analysis, both stock market data and weather data were collected, and the rationale for the specific data selection will be explained.

4.1. Stock market data

My investigation is based on companies of the Deutsche Aktienindex (DAX) 30, Mid-cap DAX (MDAX), and Small-cap DAX (SDAX). The TechDAX is not included, because recently, TechDAX companies were granted access to the MDAX and SDAX and are, thus, already incorporated in the given indices. The constitution of all three indices follows rules that are checked every quarter. Hence, for my analysis I use the companies which are contained in the first quarter of 2019. This is especially relevant for the MDAX and SDAX, which significantly change their composition regularly. A total of 121 companies is included, which is selected based on available stock market data. Data is retrieved from Datastream for a time horizon from 01 January 2009 to 28 February 2019 on a daily basis. This time frame was selected by reason of two arguments. First, it complies with time horizons used in extant research (Hirshleifer and Shumway, 2003; Shu, 2010) and second, it still comprises a relatively large set of companies, that is representative for the German business landscape. Moreover, a significant body of research has proven that the utilisation of the major index of a country serves as a representative dataset (Floros, 2008; Symeonidis et al., 2010). Therefore, the DAX, MDAX, and SDAX are suitable for an analysis of the German market.

Based on Datastream results, companies were sorted into nine industries, being Basic Materials, Consumer Cyclicals, Consumer Non-Cyclicals, Financials, Healthcare, Industrials, Telecommunication, Technology, and Utilities. The number of companies per sector is disparate which is explained through the historically shaped industrial landscape of Germany. It contains more companies in the sectors Industrials and Consumer Cyclicals than Telecommunication and Utilities as seen in Table 1. The appendix includes a list of companies in each sector for further reference.

To calculate the industry return indices, two option exists: First, the value-weighted average gives a better representation of the economy by putting more weight on companies with a larger number of outstanding shares and a higher market price per share than small companies. However, this

Table 1: Overview of the number of companies included per industry

Industry	Number of companies included
Basic Materials	14
Consumer Cyclicals	19
Consumer Non-Cyclicals	4
Financials	19
Healthcare	12
Industrials	30
Telecommunication	4
Technology	16
Utilities	3

method does not incorporate the quick growth of small enterprises and is exposed to the risk of overweighting a few incumbent companies. Second, an equally-valued approach, in turn, distributes market returns equally along with all included companies. This method benefits from higher exposure to small and medium-sized companies, which hold significant growth potential. A downturn is the missing realistic depiction of the stock-economy relation. In a considerable body of literature, both equally-and value-weighting methods have been used, but results for both cases were very similar (Cao and Wei, 2005; Kamstra et al., 2003; Saunders, 1993; Zheng et al., 2001). Zhu and Goetzmann (2003) used the equal weighted average only, because "average of the spread better reflects the average market maker's behavior" (p. 12). There are both arguments for and against the equally- and value-weighted strategy. For the calculation of the industry return indices, the equally-weighted method has been used.

The compounded returns of the industry indices have been used to receive a stationary series of stock market returns. Returns for each industry have been calculated as the change in the natural logarithm of the company price for the two successive days:

$$R_{t,j} = \ln\left(P_{t,j}\right) - \ln\left(P_{t-1,j}\right) \tag{9}$$

$P_{t,j}$ is the adjusted price at day t of industry j, incorporating stock splits and other corporate actions, apart from dividends. $P_{t-1,j}$ is the price of the previous day of industry j. This calculation is also in line with extant research (Floros, 2011; Sariannidis et al., 2016).

The data plots in Figure 2 to Figure 10 in the appendix depict the fluctuation of market returns for each of the nine industries. It can be noticed that returns are highly volatile and show evidence for volatility clustering.

4.2. Weather data

Weather data was obtained from the Climate Data Center (CDC) of the DWD. The platform offers a comprehensive set of historical data for several weather variables. For my analysis, historical weather data of Frankfurt am Main is used. The weather station with the station ID 1420 is located close to Frankfurt Airport at an altitude of 100m (8.5213, 50.059). Weather data has been collected on a daily basis for the variables: the average temperature at an altitude of 2m in °C and precipitation height in mm per square meter.

It is also necessary to address the topic of location choice. Frankfurt is one of the most important financial centres in Europe and the most important one in Germany. With Xetra and Börse Frankfurt, it inherits the largest of the seven German stock exchange. The dispersion of market participants in Germany is, compared with the US, much smaller. Consequently, Frankfurt is a good proxy for the behaviour of traders located in Munich, Dusseldorf, and Stuttgart as well (Krämer and Runde, 1997). As the weather conditions are relatively moderate all over Germany, the weather of Frankfurt is utilised as a representative for the weather in Germany. Research has moreover proven that only the largest exchange in a country determines prices, as stated by Krämer and Runde. As a result, changes in market prices in Frankfurt are representative of other exchanges. This fact also holds through the effect of arbitrage. Saunders (1993) states that traders on Wall Street might have a severe impact on security prices because they are concerned about market prices. As they work at the same location every day, a mood variable might influence traders more than geographically spread market participants. This opinion is shared by Zhu and Goetzmann (2003) who include, next to market makers, also news providers and other agents who are physically located in the exchange hosting city. The behaviour of those market participants is conjectured to be responsible for a relation between weather and return. As traders are based in Frankfurt, it appears plausible to utilise this location. For my analysis, I will not further investigate e-trading, as this process is done automatically and is probably not influenced by traders' or investors' mood.

4.3. Descriptive statistics

Table 2 below presents Pearson correlation coefficients for the nine industry indices. One can observe a strong correlation between all industry returns, which are all significant at a 1% level. Correlation between industry returns implies an interconnectedness of industries. Industry indices seem to move in lockstep with each other. The correlation is highest for Basic Materials and Industrials with 0.8792*** and lowest for Consumer Non-Cyclicals and Telecommunication

Table 2: Correlation matrix for stock market returns

	Financials	Telecommu-nication	Technology	Consumer Non-Cyclicals	Industrials	Healthcare	Basic Materials	Consumer Cyclicals	Utilities
Financials	1								
Telecommunication	.6556***	1							
Technology	.7268***	.6188***	1						
Consumer Non-Cyclicals	.5985***	.5089***	.5459***	1					
Industrials	.8424***	.6822***	.8162***	.6380***	1				
Healthcare	.6666***	.6230***	.7060***	.5883***	.7429***	1			
Basic Materials	.7966***	.6309***	.7435***	.6002***	.8792***	.6768***	1		
Consumer Cyclicals	.7925***	.6551***	.7592***	.6053***	.8703***	.7054***	.8358***	1	
Utilities	.8312***	.6977***	.8090***	.6561***	.9181***	.8534***	.9374***	.9332***	1

Note: Asterisks indicate significance as follows: (*)10%, (**) 5%, (***) 1%. In parentheses: Standard errors.

with 0.5089***. Therefore, knowing that industry return's behaviour is quite similar, it will be interesting to investigate, whether the correlation with weather is identical for all industries.

Simple summary statistics of the market return and weather data are included in my analysis. Table 3 reports market returns. It provides insight into the nature of the distribution of returns that should be analysed before proceeding with further analysis. The first column shows the mean return, which varies across industries but is always slightly positive. Nevertheless, it is not possible to reject the null hypothesis that mean returns are not statistically different from zero. Standard deviation is relatively similar across all sectors. Basic Materials returns have the highest standard deviation and consequently the highest variance in returns. The return series of all industries are strongly skewed to negative returns and leptokurtic to the normal distribution. To evaluate the goodness-of-fit, a Jarque-Bera (JB) test is conducted, to analyse whether the skewness and kurtosis of the sample data match a normal distribution. Normally distributed data would have an expected kurtosis and skewness of zero. Deviation of a normal distribution will increase the JB value. In the selected sample, JB values range from 2,240.7704*** to 13,227.4538***. The Augmented Dickey-Fuller (ADF) test confirms that the market return variables are stationary, and therefore the hypothesis that a unit root exists is rejected.

Table 4 displays statistics of the weather data. Temperature is recorded in °C and precipitation in mm per square meter. Therefore, they do not have high explanatory value when compared with each other. However, skewness is valuable for interpretation. Temperature has a negative skew, just like returns. Consequently, it might be interesting to test for correlation between those variables and market returns. Further, precipitation has a substantial skewness of 4.3147 which indicates a strongly asymmetrical distribution. Its kurtosis is also extreme with 30.5830. Therefore, precipitation exhibits tail data that exceeds the tails of a normal distribution. This is a signal that Frankfurt is sometimes exposed to intense rainfall which could potentially influence investor's behaviour.

5. Hypothesis

Market returns are the result of a complex construct of influencing factors. Generally, the price is determined by supply and demand. However, this is just a theoretical approach, and also technical factors impact stock returns. Inflation, the economic strength of the market, and competitors influence investors' sentiments, attitude, and expectations. Further political and economic decisions can induce stock market activity. Moreover, the weather has often been argued to influence stock market returns. Therefore, keeping in mind that the trader's attitude can impact investment decisions, leads me to the hypotheses I want to test with the dataset and the methods discussed:

H0: Weather variables are not correlated with stock market returns. The investor is not significantly influenced by the weather.

H1: Weather variables are correlated with stock market returns. Investors are significantly influenced by weather.

The analysis of existing research implies a possible relationship between weather and stock market returns that would implicate to reject the null hypothesis. This will be discussed in the following section six "Empirical Results" in greater detail. Additionally, the purpose of this paper is not only to identify a potential relationship between stock market returns and weather, but also to investigate whether industries are affected differently by weather. This could result either in a difference in positive or a negative correlation with respect to each industry or in equally existent correlation.

H2: Industry market returns are equally influenced by weather.

H3: Industry market returns respond significantly different to weather.

6. Empirical results

The following paragraphs will investigate the implied hypotheses after the data and methodology used for my empir-

Table 3: Descriptive statistics of stock market returns

Statistics	Financials	Telcommuni -cation	Technology	Consumer Non-Cyclicals	Industrials	Healthcare	Basic Materials	Consumer Cyclicals	Utilities
Mean	0.0005	0.0006	0.0008	0.0002	0.0005	0.0006	0.0002	0.0004	0.0004
Maximum	0.0728	0.0829	0.0725	0.0389	0.0631	0.0459	0.0803	0.0659	0.0520
Minimum	-0.0560	-0.1584	-0.0741	-0.0693	-0.0704	-0.0509	-0.0777	-0.0635	-0.0640
SD	0.0111	0.0142	0.0129	0.0100	0.0124	0.0105	0.0145	0.0118	0.0112
Skewness	-0.1965	-0.5350	-0.3526	-0.2723	-0.4000	-0.2827	-0.1475	-0.2639	-0.3041
Kurtosis	7.4156	10.8906	4.9359	5.2427	5.3707	4.4684	5.7647	5.8631	5.1275
Jarque-Bera	6,091.2391***	13,227.4538***	2,746.0117***	3,068.8088***	3,256.7562***	2,240.7704***	3,680.3264***	3,827.8807***	2,945.0084***
ADF	-47.9430***	-49.2850***	-48.6610***	-51.1070***	-46.9800***	-50.0000***	-48.8410***	-46.1710***	-47.9750***
Observations	2,651	2,651	2,651	2,651	2,651	2,651	2,651	2,651	2,651

Note: This table reports bin-test results for the equal-size sample. The sample covers the period 01.02.2009 to 28.02.2019 with a sample size of 2651 observations. All samples are in logarithmic first difference form and expressed as a percentage on a daily basis. Jarque-Bera test matches the skewness and kurtosis to the normal distribution. ADF is the Augmented Dicked-Fuller test for a unit root. Asterisks indicate significance as follows: (*) 10%, (**) 5%, (***) 1%.

Table 4: Descriptive statistics of weather data

Statistics	Temperature	Precipitation
Mean	11.1436	1.5558
Maximum	29.7000	50.2000
Minimum	-11.0000	0.0000
SD	7.5970	3.6679
Skewness	-0.0587	4.3147
Kurtosis	2.2562	30.5830
Observations	2,651	2,651

ical tests has been described, and it will summarise the outcomes of my analysis. The bin-test is discussed first. Afterwards, the results of the EGARCH model are described with the aim to find a relationship between weather and industry stock market returns. This will be done by testing two sets of variables. My study ends with a discussion of the outcomes and a further outlook.

6.1. Bin-test

The bin-test was performed for each industry separately, and results are depicted in Table 5. Generally, one can observe a negative correlation between return and temperature for seven of the nine industries. Thus, low temperatures are typically associated with greater returns than high temperatures. Financials and Telecommunication, however, show a positive correlation between returns and temperature. The percentage of positive returns is always higher for low temperatures when there is a negative correlation between returns and temperature. The z-score for differences in return means is only significant at the 5% level for Consumer Non-Cyclicals. The percentage of positive returns does not have any significant z-scores.

The results in Table 5 conform with the literature, as a negative correlation is reported in the majority of the sectors. High temperatures seem to be associated with lower returns and low temperatures with higher returns. This finding can be explained with psychological research, indicating that high temperature can cause apathy leading to lower risk-taking. Consequently, apathy must strongly dominate aggression. On the opposite, aggression is dominant on days with low temperature leading to higher risk-taking which in turn leads to greater market returns. These conjectures are in line with the findings of Cao and Wei (2005).

The return behaviour in the Financials and Telecommunication sector raises the question for the underlying reason for this anomaly and could be explained with existing literature. Both high and low temperature can induce aggressive behaviour. Therefore, contradicting with the findings derived from the majority of industries, aggression might dominate apathy in certain occasions.

6.2. EGARCH

Table 6 and 7 report estimated parameters for equation (4) and (6) as outlined in section 3.2. Table 6 depicts estimates for the variance equations, having the underlying mean equation which is displayed in Table 7 with respective mean equations' estimates for each industry. The analysis has been conducted by using an EGARCH (1,1) model with GED. The reason for choosing this method is that the variance of stock-market returns varies over time and is dependent on past performance which has been further explained in section 3.2.

First, I will analyse the variance equation that offers insights into the distribution and behaviour of stock market returns. The persistence in conditional volatility, measured by γ_l, is highly significant and mostly has positive coefficient values close to one. Therefore, it is evident that GARCH effects are apparent in the German stock market and stock market

Table 5: Bin-test results

		Bin 1	Bin 2	Bin 3	Bin 4	z-score(4,1)
Financials	Return mean	0.00040	0.00053	0.00035	0.00062	0.20866
	% of pos. returns	0.53623	0.53800	0.52330	0.54912	0.26165
Telecommunication	Return mean	0.00034	0.00090	0.00040	0.00053	0.13921
	% of pos. returns	0.50000	0.52000	0.52061	0.50882	0.17844
Technology	Return mean	0.00124	0.00102	0.00076	0.00038	-0.68063
	% of pos. returns	0.52899	0.53100	0.53405	0.53652	0.15287
Consumer Non-	Return mean	0.00062	0.00018	0.00036	-0.00062	-1.26603
Cyclicals	% of pos. returns	0.55072	0.49700	0.50538	0.46851	-1.67111**
Industrials	Return mean	0.00071	0.00065	0.00035	0.00031	-0.34299
	% of pos. returns	0.57246	0.55100	0.52867	0.53401	-0.78498
Healthcare	Return mean	0.00073	0.00058	0.00073	0.00007	-0.71451
	% of pos. returns	0.55072	0.52100	0.54839	0.50630	-0.90264
Basic Materials	Return mean	0.00042	0.00027	0.00006	0.00023	-0.13717
	% of pos. returns	0.51449	0.48900	0.49552	0.51134	-0.06393
Consumer Cyclicals	Return mean	0.00021	0.00041	0.00064	-0.00014	-0.31193
	% of pos. returns	0.55797	0.51200	0.52419	0.51889	-0.79505
Utilities	Return mean	0.00045	0.00042	0.00048	0.00005	-0.38838
	% of pos. returns	0.56522	0.52700	0.53226	0.52393	-0.84120

Note: This table reports bin-test results for the equal-size sample. The sample covers the period 01.02.2009 to 28.02.2019 with a total of 2651 observations. The mean return and the percentage of positive returns are reported for each of the four bins. Z-scores are computed as follows: $z\_score^{mean}_{4,1} = \left(\mu_4 - \mu_1\right) / \sqrt{\frac{\sigma_4^2}{n_4} + \frac{\sigma_1^2}{n_1}}$ and $z\_score^{frequence}_{4,1} = \left(p_4 - p_1\right) / \sqrt{\frac{p_4(1-p_4)}{n_4} + \frac{p_1(1-p_1)}{n_1}}$ Asterisks indicate significance as follows: (*)10%, (**) 5%, (***) 1%.

Table 6: Estimates for the conditional variance

Coefficient	Financials	Telecommunication	Technology	Consumer Non-Cyclicals	Industrials	Healthcare	Basic Materials	Consumer Cyclicals	Utilities
α_0	-0.1907***	-3.2453***	-0.4332***	-0.2907***	-0.3863***	-0.6388***	-0.0926***	-0.2059***	-0.2836***
	(0.0395)	(0.6492)	(0.0854)	(0.0812)	(0.0681)	(0.1178)	(0.0235)	(0.0476)	(0.0530)
α_1	0.1541***	0.3920***	0.1612***	0.1192***	0.1781***	0.1610***	0.0969***	0.1646***	0.1580***
	(0.0199)	(0.0728)	(0.0242)	(0.0228)	(0.0231)	(0.0276)	(0.0151)	(0.0214)	(0.0215)
ξ_0	-0.0937***	-0.1055***	-0.1004***	-0.0511***	-0.1343***	-0.1291***	-0.0898***	-0.0801***	-0.1204***
	(0.0121)	(0.0447)	(0.0164)	(0.0136)	(0.0152)	(0.0188)	(0.0106)	(0.0141)	(0.0149)
γ_1	0.9792***	0.6148***	0.9506***	0.9683***	0.9570***	0.9306***	0.9892***	0.9768***	0.9690***
	(0.0043)	(0.0775)	(0.0097)	(0.0088)	(0.0075)	(0.0127)	(0.0027)	(0.0052)	(0.0058)
ν	1.4203***	0.8780***	1.4870***	1.3938***	1.4283***	1.4531***	1.5798***	1.3506***	1.4867***
	(0.0551)	(0.0301)	(0.0583)	(0.0430)	(0.0591)	(0.0593)	(0.0674)	(0.0405)	(0.0622)
Log-likelihood	8629.7920	7778.1860	7986.2680	8602.1610	8250.7640	8528.4020	7836.6410	8370.9450	8491.2720
Adj. R^2	0.0039	0.0011	0.0025	-0.0002	0.0077	0.0003	0.0019	0.0107	0.0042

Note: This table presents parameter coefficients for the EGARCH(1,1) specification in order to estimate the conditional variance. The model is based on the conditional variance equation (6): $\ln\left(\sigma_t^2\right) = \alpha_0 + \sum_{l=1}^{p} \gamma_l \ln \sigma_{t-1}^2 + \sum_{l=1}^{q} \alpha_l \left[|z_{t-l}| - E|z_{t-l}|\right] + \sum_{l=1}^{q} \xi_l z_{t-l}$. Asterisks indicate significance as follows: (*)10%, (**) 5%, (***) 1%. In parentheses: Standard errors.

volatility is highly dependent on the previous period. Also, the magnitude effect α_l is highly significant, implicating that the size of shock influences the stock market response. However, the values are relatively small, which translates into a short memory of variance. ξ_l, measures the leverage effect. Its values are negative and highly significant for all industries, implicating that an asymmetrical response to past residuals is observed. Thus, higher volatility is perceived for negative shocks than for positive shocks of the same magnitude. This observation indicates that investors are more influenced by negative compared to positive news. This fact could be translated to weather news, and consequently, especially high and low temperatures should be tested.

Further, the endogenously estimated shape parameter v

Table 7: EGARCH parameter estimates

Coefficient	Financials	Telecommu-nication	Technology	Consumer Non-Cyclicals	Industrials	Healthcare	Basic Materials	Consumer Cyclicals	Utilities
b0	0.0010***	-0.0004	0.0011***	0.0005 *	0.0012***	0.0008***	0.0007 **	0.0008***	0.0009***
	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
b1	0.0679***	0.0377***	0.0514***	-0.0111	0.0761***	0.0046	0.0517***	0.0941***	0.0555***
	(0.0191)	(0.0146)	(0.0195)	(0.0186)	(0.0196)	(0.0194)	(0.0197)	(0.0190)	(0.0196)
b2	-0.0000**	0.0001***	-0.0000	-0.0000*	-0.0001**	-0.0000	-0.0001**	-0.0000	-0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
b3	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0000)

Note: The estimated parameters rely on the model, eq.(4): $R_{t,j} = b_0 + b_1\sigma_t^2 R_{t-1,j} + b_2\sigma_t^2 Temp_t + b_3\sigma_t^2 Prec_t + \xi_{t,j}$. Parameters are estimated simultaneously with eq. (6): $\ln\left(\sigma_{t,j}^2\right) = \alpha_0 + \sum_{l=1}^{p}\gamma_l \ln\sigma_{t-1,j}^2 + \sum_{l=1}^{q}\alpha_l\left[\left|z_{t-1,j}\right| - E\left|z_{t-l,j}\right|\right] + \sum_{l=1}^{q}\xi_l z_{t-l,j}$ Asterisks indicate significance as follows: (*)10%, (**) 5%, (***) 1%. In parentheses: Standard errors.

shows that we can reject a normal or Laplace distribution for all industries except the Telecommunication sector. As $\nu < 2$, the tails are heavier than in a normal distribution. The distribution is leptokurtic and has positive excess kurtosis. Values are all significant at a 1% level, and range between 0.8780*** and 1.3506***. This implies a distribution that is more similar to Laplace than to a normal distribution. The distribution of Telecommunication is smaller than zero, while all other industry indices return values are greater than zero. The rationale behind this is that the sample size forming the industry index is very small and object to flaws.

The adjusted R^2 differs across industries. On average, the previous day's market return and weather data explain 0.36% of the market return. Weather explains only a minimal amount of market returns. In terms of magnitude and pattern, the adjusted R^2 is in line with research by Saunders (1993), Cao and Wei (2005) and Kamstra et al. (2003). Explanatory power is greatest for Consumer Cyclicals with 1.07% and smallest for Consumer Non-Cyclicals with 0.00% displaying that this model has no predictive value for this particular industry.

In the following, I will present results for the mean equation and analyse whether market returns are correlated with the weather variables, temperature and precipitation and if the relationships are significant.

Overall, the model affirms the existence of a relationship between weather and stock market returns. The lagged market return value is highly significant and positive for all industries. This finding goes hand in hand with the EGARCH model choice, as it proves the conjecture that past returns influence today's returns.

Temperature is also significantly correlated with industry index returns when considered together with precipitation. The coefficient parameter b2 is mostly negative and highly significant. Values are all close to zero and range from 0.00005*** for Telecommunication to -0.00006** for Basic Materials. The coefficients for Telecommunication and Financials are significant at the 1% level, the values for Industrials and Basic materials at the 5% level, and the coefficient for Consumer Non-Cyclicals and Utilities at the 10% level. Consequently, traders are influenced by temperature to a different extent depending on the industry. The small parameter coefficients come as no surprise and are in line with existing research, which frequently reports very small coefficient values for weather variables (Saunders, 1993). The fact that temperature mostly has a negative effect on market returns is in agreement with previous findings (Cao and Wei, 2005; Floros, 2011, 2008; Keef and Roush, 2002). To illustrate the economic significance inherited in the temperature effect, I will include an example that shows how daily returns react to a temperature shock of one standard deviation. The standard deviation for temperature measured in Frankfurt is 7.5970°C; the coefficient of temperature for Industrials is -0.00005. Consequently, the return impact of one standard deviation of temperature is 0.0004.

The one standard deviation impact, thus, is three-quarters of the average daily return for the Industrials index.

Apart from temperature, precipitation is included in the model, which has a slightly positive, but no significant, effect on market returns. Hirshleifer and Shumway (2003) have also brought up evidence for the insignificance of rain on stock market returns.

In conclusion, according to this model, the null hypothesis, that weather variables and stock market returns are not correlated, can be rejected. My analysis provides evidence that traders are influenced by temperature and the past performance of stock prices. Further, the hypothesis that industry market returns are equally affected by weather is rejected as well. My outcomes reveal that significance in return depends on the industry.

6.3. Robustness test

My analysis has made use of an EGARCH model. As part of a thorough review, the robustness of the EGARCH model and regression must be examined. I will perform a robustness test for the EGARCH model, and for the regression analysis.

First, a likelihood ratio (LR) test was conducted to verify the relative explanatory power of the EGARCH model. The underlying equation for the LR test is as follows:

$$\mathrm{LR} = -2 * (L_0 - L_1) \tag{10}$$

LR is based on a chi-squared distribution, with L_0 being the likelihood function used under the null hypothesis and L_1 corresponding to the alternative hypothesis. The test, which is also called deviance, measures the difference in the LR of the nested model to more sophisticated models. The GARCH model is considered the nested model, L_0 and the alternative GARCH specifications are treated as L_1. The smaller the absolute difference, the better the model fit. Table 8 illustrates the log likelihood values of each model and Table 9 the LR ratio test. LR is smallest for the EGARCH model, supporting my model choice. Additionally, for all industries, apart from Telecommunications, the EGARCH model yields the highest log-likelihood values. Therefore, this model has the best fit and verifies the robustness of the model choice.

Secondly, I consider an alternative regression function for the EGARCH model which incorporates a calendar related anomaly to achieve a sufficient robustness test. I have chosen the Monday effect, also called the weekend effect, because it has been employed in a variety of research (Floros, 2008; Hirshleifer and Shumway, 2003). Studies have shown that the Friday closing price has an influence on the Monday opening price (Rogalski, 1984). Therefore, this effect has been added to the mean equation (4). The Monday effect is incorporated as a dummy variable D_{Mon}, being one for the day Monday and zero otherwise. It yields the regression equation:

$$R_{t,j} = b_0 + b_1 R_{t-1,j} + b_2 Temp_t + b_3 \,\mathrm{Prec}_t + b_4 D_{Mon} + \xi_t \tag{11}$$

After controlling for this effect, the regression results should remain similar in order to achieve robustness in the utilised model. Indeed, temperature remains a significant variable after the dummy variable is added. Only Telecommunication does not report a significant correlation with weather anymore. Precipitation is still insignificant for all industries. Also, the day Monday, as the beginning of the trading week, does not influence stock market returns. The insignificance of the Monday effect contradicts the majority of existing research. However, it is in line with the findings of Krämer and Runde (1997), who analysed the German DAX returns and did not find any significant effect for specific days or the week.

In summary, the regression robustness test, my model is robust against the Monday effect. The temperature correlation coefficient remains negative for all industries and significant for the majority of sectors. Consequently, the EGARCH model has high informative value.

7. Discussion

From the empirical results, which have been discussed in detail, it can be conclude that temperature impacts stock market returns of particular industries. Observations from the underlying dataset identified Financials, Consumer Non-Cyclicals, Industrials, Basic Materials, and Utilities as industries that have a significant negative correlation between temperature and stock market performance. This chapter will elaborate on possible reasons for the observed relationship in the industries mentioned above and focuses on the analysis of economic impacts. It has been extensively discussed in section 2 that weather impacts mood, decision-making, and consequently investment decisions and risk- taking behaviour of traders. In addition to this effect, weather influences companies' economic performance. This effect is partially factored into the market price, but the extent to which investors are subconsciously influenced by weather effects is unknown. Therefore, I conjecture that both effects are subliminally integrated into the behaviour of traders and are therefore relevant aspects in the discussion.

Hot and cold temperature can influence several industrial areas. This paragraph will outline economic reasons, why low temperature leads to higher market returns and vice versa. The Industrials industry consists of companies in the logistics area, machinery, aviation, construction, and many more. Focussing on aviation, companies as Lufthansa are affected in their daily business by high temperatures. The take-off performance is negatively affected, because the air density decreases, the aeroplane will climb slower, leading to delays and requiring more fuel. The same problem exists for many logistics companies. In addition, extremely hot weather induces physical activity to be especially strenuous and is harmful to workers' health constitution and performance.

The Basic Material sector is very energy intensive. Especially in summer, machines need to be cooled down, which increases energy consumption and consequent energy costs.

In the Utilities industry, the primary energy sources are predominantly used for heating. Thus, low temperatures can be favourable because demand rises which in turn increases revenue.

For Consumer Non-Cyclicals, the interpretation is not as intuitive as for the other sectors. My sample includes industries active in the food producing sector (Suedzucker), growers and seed producers (KWS), personal care (Beiersdorf), and the Baywa group, which is active in agriculture, energy, and building materials. This sample, thus, still includes companies engaged in different fields. Therefore, my interpretation concentrates on the agricultural companies Baywa and KWS. The former benefits from the advantages of low temperatures for the same reasons as Utilities companies. This could outweigh the effect that increasing fruit and vegetable consumption is expected for higher temperatures. The latter might be influenced by hot spells implicating declining seed sales volume. The economic performance of Suedzucker might depend on the growth of the sugar beet. This argumentation is not exhaustive, and no reasonable explanations can be found for temperature implicationson the economics of Beiersdorf.

Turning to the Financial industry, my conjectures are

Table 8: Loglikelihood values

Statistics	Financials	Telecommu-nication	Technology	Consumer Non-Cyclicals	Industrials	Healthcare	Basic Materials	Consumer Cyclicals	Utilities
GJR	8463.963***	7764.910***	7904.216***	8562.111***	8092.710***	8457.401***	7647.490***	8211.179***	8326.612***
PARCH	8456.612***	7759.040***	7888.662***	8560.148***	8080.146***	8448.126***	7642.939***	8208.130***	8318.698***
GARCH	8607.276***	7836.726***	7972.032***	8588.664***	8216.340***	8506.574***	7805.412***	8355.436***	8458.939***
NARCH	8467.850***	7764.164***	7905.959***	8561.830***	8096.731***	8456.661***	7650.093***	8213.454***	8328.849***
EGARCH	8629.792***	7778.186***	7986.268***	8602.161***	8250.764***	8528.402***	7836.641***	8370.945***	8491.272***

Note: This table reports the log-likelihood values with respect to the selected GARCH model: GJR GARCH, Power ARCH (PARCH), Nonparametric ARCH (NARCH), EGARCH. In highlighted numbers indicate the greatest log-likelihood value per industry. Asterisks indicate significance as follows (*) 10%, (**) 5%, (***) 1%.

Table 9: Likelihood ratio statistics

Statistics	Financials	Telecommu-nication	Technology	Consumer Non-Cyclicals	Industrials	Healthcare	Basic Materials	Consumer Cyclicals	Utilities
GJR	-286.626***	-143.632***	-135.632***	-53.106***	-247.260***	-98.346***	-315.844***	-288.514***	-264.654***
PARCH	-301.328***	-155.372***	-166.740***	-57.032***	-272.388***	-116.896***	-324.946***	-294.612***	-280.482***
NARCH	-278.852***	-145.124***	-132.146***	-53.668***	-239.218***	-99.826***	-310.638***	-283.964***	-260.180***
EGARCH	45.032***	-117.080***	28.472***	26.994***	68.848***	43.656***	62.458***	31.018***	64.666***

Note: This table illustrates the LR statistic in order to test the significance of the models (GJR, PARCH, NARCH, and EGARCH) to the nested model GARCH. The LR statistic is calculated as follows: LR=-2*(L_0-L_1). Asterisks indicate significance as follows: (*) 10%, (**) 5%, (***) 1%.

Table 10: EGARCH robustness test including seasonality related anomaly variable

Coefficient	Financials	Telecommu-nication	Technology	Consumer Non-Cyclicals	Industrials	Healthcare	Basic Materials	Consumer Cyclicals	Utilities
b0	0.0010 ***	0.0005 ***	0.0010 ***	0.0004	0.0012 ***	0.0040 **	0.0006 *	0.0008 ***	0.0002 ***
	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0194)	(0.0003)	(0.0003)	(0.0003)
b1	0.0679 ***	0.0520	0.0512 ***	-0.0125	0.0762 ***	-0.0000	0.0517 ***	0.0941 ***	0.0550 ***
	(0.0191)	(0.0176)	(0.0195)	(0.0186)	(0.0195)	(0.0000)	(0.0197)	(0.0190)	(0.0196)
b2	-0.0000**	-0.0000	-0.0000	-0.0000*	-0.0001**	0.0000	-0.0001**	-0.0000	-0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
b3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0006	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0004)	(0.0001)	(0.0000)	(0.0000)
b4	0.0001	0.0007	0.0004	0.0006	0.0001	0.0006	0.0002	0.0000	0.0002
	(0.0004)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0003)	(0.0005)	(0.0004)	(0.0004)

Note: The estimated parameters rely on the model, eq. (11): $R_{t,j} = b_0 + b_1 R_{t-1,j} + b_2 Temp_t + b_3\, Prec_t + b_4 D_{Mon} + \xi_{t,j}$. Parameters are estimated simultaneously with eq. (6): $\ln\left(\sigma^2_{t,j}\right) = \alpha_0 + \sum_{l=1}^{p} \gamma_l \ln \sigma^2_{t-1,j} + \sum_{l=1}^{q} \alpha_l \left[\left|z_{t-l,j}\right| - E\left|z_{t-1,j}\right|\right] + \sum_{l=1}^{q} \xi_l z_{t-1,j}$. Asterisks indicate significance as follows: (*) 10%, (**) 5%, (***) 1%. In parentheses: Standard errors.

mainly based on the findings of Subak et al. (2000). By analysing the implications of the anomalously hot weather during summer in 1995 in the UK, they find that the recorded insurance claims for property damage through subsidence were much higher than for bursting pipes. Soil subsidence is a natural cause of lasting drought and heat. Furthermore, outdoor fires are sometimes caused by heatwaves, increasing the number of insurance cases. Consequently, high-temperature periods constitute a less economically profitable scenario for companies in this sector, than more moderate weather circumstances.

It has been previously reported in the literature that climate changes, in particular temperature, can impact the economic dimension in the Telecommunications sector (Adams and Steeves, 2014). Specifically, high temperatures lead to more need for I equipment cooling in base stations or exchanges, which can result in an escalating failure rate. Also, malfunction and reduced life span of network-and telecommunication equipment are possible. Energy demand increases as a result of intensified cooling activities and might lead to a rise in energy prices. These are, among others, reasons explaining why high temperatures are harmful to companies in the telecommunication sector.

Taken together, industry performance is impacted by climate conditions. However, the argumentation outlining why low temperatures are favourable for business performance and high temperatures harm the industrial segment is one-sided, and it must be noted that the effects of climate can also be opposing. In other words, there are numerous unfavourable implications of cold weather.

Another relevant aspect of this topic is the psychological implication for investor behaviour. As a result of the economic impact I conjecture that these complex correlations between temperature and stock markets are triggered intuitively in market makers. Thus, on days with hotter temperatures traders subconsciously incorporate the environmental circumstances into their evaluation of the respective industries. In addition, they also consider these factors in their investment decisions.

8. Conclusion

My findings are essential to understand the implications of weather on stock market returns. The gained knowledge could be insightful for developing weather-based trading strategies. To derive a benefit from this strategy, transaction costs need to be very low because the correlation coefficient of stock market returns is minimal and consequently, economic gains are marginal (Hirshleifer and Shumway, 2003). Another finding of this paper is that it raises the general awareness that people are likely to be influenced by climate factors. If traders, or investors, know that their investment decisions might be impacted by the outside temperature, ill-conceived investments could be prevented.

8.1. Outlook and limitations

Additionally, seven caveats must be addressed that concern potential flaws in methodology and data choice. First, the investor location must be addressed. By choosing Frankfurt, I can depict the behaviour of traders. This does not include independent market makers or individual investors who are widely distributed in Germany and over the whole world (Sariannidis et al., 2016). If order-submitting investors are price setters, and investors' mood is affected by weather, Frankfurt is not a good proxy and can potentially deteriorate results. This limitation could be addressed by calculating a population-weighted temperature based on the greatest German cities (Cao and Wei, 2002), but as investors are not limited to Germany, this is not a sound solution.

Second, traders usually work in office buildings which are furnished with air cooling as well as heating systems. Indoor temperature levels are retained at a medium temperature of approximately 21°C. If the temperature does correlate with human behaviour and market returns, this occurrence is confined to the extent to which traders are exposed to the outside temperature, e.g., during their commute. Accordingly, it is "the psychological imprint of the extreme temperature that mediates people's mood and influences their behaviour" (Cao and Wei, 2002, p. 1562). Nevertheless, it remains questionable whether the exposure to the outside environment is significant enough to utilise temperature as a regression variable.

Third, other economy-related variables could be included in the regression model because it is evident, that weather, if at all, only explains a vanishing small portion of market return behaviour. Especially, variables related to global environmental emissions might affect stock market returns (Sariannidis et al., 2016).

Fourth, weather and the economy are dynamic, and climate anomalies are never alike. Therefore, it is not reasonable to draw implications out of a climate anomaly to a future period.

Fifth, the researchers Krämer and Runde (1997) claim that findings of Saunders could also be a result of a type one error due to statistical inference. This flaw could be limited by collecting data from a longer period of time than ten years. Further, they claim that the significance of a correlation between the variables weather and market returns is subject to data mining. Depending on the definition of good and bad weather, relationships can either be identified or dismissed. Zheng et al. (2001) also share this view. They claim that by studying historical stock market returns one can find significant relationships just by chance.

Sixth, existing research has mostly focused on global or national stock market indices that do not differentiate between industries. As my analysis has proven, correlations do only exist for specific industries. Thus, by combining all sectors in an index, the weather effect is diluted because significant and insignificant industries are combined. This fact could explain why researchers obtain diverging results and would challenge the outcome correctness of extant work.

Seventh, no psychological literature exists that directly analyses the impact of weather on investment behaviour. This lack of research has already been pointed out by Cao and Wei (2002). The conjunction is generally made by financial researchers that extrapolate from feelings and mood to investment activities. Consequently, it is questionable whether a direct link between weather and market returns exists. One needs to strictly differentiate between correlation and causation. My paper could only prove correlation which does not guarantee any causal relations. This limitation is based on potential endogeneity problems within the model implicating that an independent variable is potentially correlated with the error term. Three sources of endogeneity will be briefly discussed.

It is difficult to avoid omitted variables. Uncontrolled variables can be correlated with both independent and dependent variables or independent variables and the error term. The confounding variables lead to inconsistent estimates and biases. I cannot rule out the existence of omitted variables from my model. Another source of endogeneity is the simultaneity bias which means that the explanatory and dependent variable are jointly determined. This bias is unlikely as weather is not caused by stock market but by meteorological dynamics. Additionally, measurement errors of the dependent variable can result in inconsistent parameter estimates. Market returns can be calculated based on various methods. The prices and returns chosen in this model might be prone to errors. Instrumental variables, among other techniques, can be utilized to address the problem of endogeneity. However, completely exogenous instruments are very difficult to find.

All limitations suggest that more research is needed in this field, in particular, with respect to the analysis of weather implications on industry returns. Especially, this field should be evaluated on a global level as has been done in research that investigated the relationship of a variety of global indices with weather. Besides, further studies should incorporate a finer depiction of weather data and incorporate individual and institutional investors into the model. Hitherto, only weather and seasonal variables have been included in research. The literature is outdated to a great extent. On the one hand, one could argue, that volatility in weather does not change. On the other hand, global warming is increasingly getting public attention. Hence, it would be interesting to connect market returns not only with weather but include a climate change variable that depicts profound variations in weather trends and influences mood to a yet unknown extent. This procedure is also valuable, considering that climate change has already had major implications on industry standards and policies, as the automotive industry has illustrated (Williams et al., 2018).

8.2. Final remarks

In the psychological literature, it is well established that weather can influence people's mood and feelings. Mood, in particular, impacts people's decision-making behaviour. From a financial point of view, mood also impacts investment-decisions and risk assessment. The empirical literature has identified temperature as one of the most critical weather variables that affect human behaviour and mood: Low temperature can cause aggression, high temperate might induce apathy. These mood alternations can lead to either higher or lower risk attitude. A body of empirical literature has revealed a relationship between weather and market returns. Examples are sunshine (Saunders, 1993), temperature (Cao and Wei, 2005), length of the night (Kamstra et al., 2003), and many more.

It is examined if weather alternates mood and investment behaviour. This is done by analysing the relationship between market returns and the weather variables temperature and precipitation. For this, a Bin-test and an EGARCH model are applied. First, I hypothesise that weather variables are correlated with stock market returns. Market returns include the German indices DAX 30, MDAX, and SDAX and are separated by industries. I consider the second hypothesis: Industry returns respond significantly differently to the weather.

After the examination of the industry indices, I can provide evidence that traders are influenced by temperature and the past performance of stock prices. The correlation between temperature and stock market returns is negative and significant for six out of nine industries. Lagged returns are all significant and mostly positively correlated with stock market returns. Precipitation, on the other hand, is not significantly correlated with stock market returns. The significance in return depends on the industry which supports the hypothesis that industry market returns do not respond equally to weather effects. The industries Technology, Healthcare, and Consumer Cyclicals do not show a significant correlation. However, for the other six industries, a significant negative correlation between temperature and stock market returns was identified. This relationship is robust to changes in the underlying model and seasonal anomalies as the Monday effect.

All in all, temperature has a negative relationship with some industries. Future research should elaborate on the underlying reasons, why particular industries' market returns are affected by weather variables. Furthermore, studies on an industry-wide level should be extended to a global scale.

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