THE INFLUENCE OF WEATHER CONDITIONS ON THE HELSINKI STOCK EXCHANGE

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ABSTRACT

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Abstract

A connection between weather conditions and the mood of individuals has been established by numerous psychological studies. Moreover, mood seems to play a role in people's decision-making processes and thus weather conditions may have an indirect influence on stock market returns. In our study based on regression analysis, we investigate the relationship between eight weather variables (precipitation, snow depth, average temperature, maximum temperature, minimum temperature, solar radiation, cloud cover and day length) and the returns of the OMX Helsinki Price Index from January 2000 to December 2019. In addition, we test whether the economic environment plays a role in the influence of weather on stock returns as investors might adapt their behavior depending on the prevailing economic conditions. Therefore, we break the 20-year period into four shorter time periods coinciding with the time before the subprime crisis, during the subprime crisis, after the subprime crisis and during the negative interest rate period. Furthermore, in addition to analyzing the absolute daily values of the weather variables, we also compare the daily values with an average of the preceding week based on the idea that for instance a sunny day is most likely to lift people's mood after a week of bad weather. We find no conclusive answer as to whether the returns of the OMX Helsinki Price Index are influenced by changes in daily weather in Helsinki. Although our results show negative correlation between solar radiation and stock returns, we conclude that the reason for this is that stocks tend to go down in summer and thus there is no causal relation between high levels of sunshine and decreased returns. Our most promising findings are the negative correlation of precipitation and cloudiness and the positive correlation of snow depth. Even though we find some statistically significant correlation, the coefficients are extremely small, indicating that the possible economic impact of these weather variables on the OMX Helsinki index is very mild at best. In conclusion, our results do not confirm any significant impact of local weather on the Helsinki Stock Exchange, but they do not provide conclusive evidence in favor of the null hypothesis either. It is possible that improved methodology or different weather data would yield more conclusive results.

Key words

Behavioral finance, stock market, stock returns, weather, mood

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1 INTRODUCTION

In this paper, we study the influence of weather conditions on the Helsinki Stock Exchange. Traditional finance theories assume that people's behavior is based on rational decision-making. If this were true, factors such as weather should have no influence on investor behavior and there would be no premise for our study. Yet, there are clear examples, such as the Dutch Tulip bubble (also known as the tulip mania), that prove that people's behavior can be far from rational. Acknowledging irrationality as a natural human trait has given rise to a new field of economic research called behavioral economics. Our study is conducted on a subfield of behavioral economics, namely, on the field of behavioral finance, which focuses on the psychological factors and biases affecting the behavior of investors and financial practitioners. Behavioral finance is a young field which was formally born in the 1980s, but at the same time it is one of the most dynamic, rapidly growing and promising fields of economic research by its scope and size. (Prosad, Kapoor & Sengupta, 2015) Interest towards behavioral economics has grown even more since 2017 when Richard H. Thaler was awarded the Nobel prize "for his contributions to behavioural economics" (Cialdini, 2018; Nobel Media AB, 2020). For these reasons, we see behavioral finance as an extremely interesting and current area of research.

Behavioral economists acknowledge that emotions affect financial decision-making in many ways. Loewenstein, Weber, Hsee and Welch (2001) have divided these ways into three categories: back-ground mood, anticipatory emotions (immediate visceral reactions) and anticipated emotions (expected future feelings). Our study focuses on the first one: the mood. In addition, we have chosen weather as the mood-altering factor. Numerous studies suggest that weather conditions, such as cloud coverage, temperature and length of day, can affect people's mood and therefore also their financial behavior (Zaleskiewicz 2006).

The goal of our study is to establish whether different weather variables influence the returns of the OMX Helsinki Price Index. There are many studies that show that weather can affect the mood of investors, thus changing their decision-making and behavior. Therefore, our hypothesis is that the returns of the OMX Helsinki index correlate with the local weather in Helsinki. Similar kinds of studies have been conducted on many stock exchanges around the world. Kaustia and Rantapuska (2015) have studied the influence of weather on investor behavior in Finland, but to our knowledge, ours is the first study analyzing the relationship between weather conditions and stock returns in Finland. A special characteristic to our study is that we analyze the weather, not only as absolute values of individual days, but also by putting those values into context and comparing them to the weather of the preceding week.

Our weather data consists of two different datasets. The first dataset includes eight weather variables: precipitation, snow depth, average temperature, maximum temperature, minimum temperature, global solar radiation, cloud cover and day length. These variables are measured as daily total values (e.g. total amount of rain in a day) or as average values (average cloud cover of a day). While these values represent absolute quantities, our second dataset consists of relative quantities. They are calculated by comparing the absolute daily values to an average of the preceding seven days. The reason why we are also using relative values is Helson's adaptation-level theory, which claims that people are more likely to evaluate changes in comparison to a reference point than absolute values. In other words, a sunny day is most likely to lift people's moods after a week of bad weather.

As financial data, we use the OMX Helsinki Price Index which is the general index comprising all the stocks listed in the Helsinki Stock Exchange. The empirical part of our study is conducted using OLS regression method. For the analysis, we have chosen a time period of 20 years from January 1, 2000 to December 31, 2019. In addition to the full time period, we run tests for four shorter periods: before to the subprime crisis, during the subprime crisis, after the subprime crisis, and during the negative interest rate period. We assume that the economic situation of the country affects how people think and feel, and therefore, investor behavior might vary between the analyzed time periods. It will be interesting to see whether weather's impact on stock returns is stronger or otherwise different during different economic situations.

This paper consists of a theoretical and an empirical part. Chapters 2–4 provide a theoretical framework for our study. We begin by explaining the traditional and behavioral approaches to human rationality and financial markets. Next, we discuss weather's diverse effects on mood and how weather has been found to influence people's behavior. The last theoretical chapter presents some key findings of previous research concerning weather's influence on stock markets. Then we move on to the empirical part of our paper. First, we introduce our data and methodology in detail in Chapter 5. In following chapter, we present the results of our empirical study and analyze the findings by comparing them with previous research. In the final Chapter 7, we summarize the results of our study and draw the conclusions.

2 ECONOMIC THEORY

The neoclassical economic theory has prevailed for decades. According to this traditional approach, investors are fully rational and markets are efficient. Under these conditions, it is impossible for weather to impact stock returns. Yet, traditional theory has not been able to fully explain some aspects of human behavior. This has given rise to a new field of study called behavioral economics which focuses on the influence of psychological factors on the decision-making processes and behavior of economic agents. This new behavioral approach allows researchers to study the possibility that stock prices could indeed fluctuate depending on weather conditions. In the following subchapters, we discuss the key concepts of the neoclassical and behavioral economic theories.

2.1 Neoclassical economics

2.1.1 Theoretical background

Rationality is one of the key concepts of neoclassical economics as it assumes that economic agents are rational. In general, rational people are expected to know their preferences and their choices should be consistent with those preferences. The rational choice theory is based on three assumptions:

(1) humans have selfish preferences,
(2) individuals maximize their own utility (i.e. satisfaction), and
(3) they act based on perfect information.

Different variants of the rational choice theory comply with these assumptions to varying degrees. Neoclassical versions of the theory assume full rationality of individuals, meaning that people are fully informed about all their options, the consequences of different decisions, as well as the probability of each outcome. In addition, people have no cognitive limitations in the perception or processing of information. (Wittek, 2013)

Assuming that individuals behave rationally has two consequences. Firstly, when people receive new information, their beliefs are updated accordingly as described by Bayes' law. Secondly, based on their beliefs, people make normatively acceptable choices that are consistent with the expected utility hypothesis. The expected utility hypothesis is a theory on people's preferences toward choices that have uncertain outcomes. Although the outcomes of the choices are uncertain, the likelihood of each outcome is known. Thus, the expected utility hypothesis states that when an individual has to choose between outcomes with different levels of probability, the optimal decision is the one that generates the highest expected utility. In other words, individuals base their decisions on cost-benefit calculations and choose the alternative that maximizes their expected utility. The expected utility can be calculated by multiplying the subjective utility (value to the individual) of each possible outcome of the decision by the probability of that outcome occurring, and then summing up those values. Since the von Neumann–Morgenstern utility function incorporates a risk assessment, people's individual attitudes toward risk explain their differing behavior under uncertain conditions. On the other hand, if the probabilities of the outcomes resulting from each choice are unknown, Savage's theory of subjective expected utility can be applied. According to Savage, the subjective expected utility can be calculated using people's subjective beliefs about the probabilities of different outcomes. (Barberis & Thaler, 2003: 1055–1056; Moscati, 2016; Abdellaoui & Wakker, 2020)

The premise that investors make rational choices is one of the cornerstones of the efficient market hypothesis. The efficient market hypothesis was introduced by Eugene Fama and Paul Samuelson simultaneously in 1965. With minor differences in their theories, both authors explained the random character of prices as a consequence of rational behavior. (Delcey, 2019) During the following decades, Fama and numerous other academics continued to develop the efficient market hypothesis which became the central proposition of neoclassical finance for many decades. The hypothesis defines an efficient financial market as a market in which security prices always fully reflect all available information and claims that real-world financial markets are efficient according to this definition. (Shleifer, 2000).

In addition to investor rationality, the efficient market hypothesis relies on few additional arguments. Firstly, since investors are rational, they value security prices rationally based on all available information. Secondly, even if some investors behaved irrationally, their trades are random and therefore cancel each other out without affecting the prices. Thirdly, any further irrationality that could influence the prices is cancelled out by the acts of rational arbitrageurs. Competition between arbitrageurs for superior returns ensures that the prices are quickly adjusted to their fundamental values. Consequently, stocks always trade at fair value and it is impossible for investors to buy undervalued stocks or sell overvalued stocks. In addition, there are no market frictions or transaction costs that interfere with trade. All relevant information is freely available and rational investors are trying to predict future stock prices using new information. The conclusion is that only unpredicted new information would cause the stock prices to react. However, Fama also proposed in 1970 three forms of market efficiency, known as the weak, semi-strong and strong forms, that determine what level of stale information allows earning superior risk-adjusted profits. In the weak form, the security prices reflect available information on the past prices and returns. In the semi-strong form, the prices reflect all publicly available information (such as, announcements on stock splits and financial reports), whereas the strong-form efficiency covers also insider information. (Shleifer, 2000; Fama, 1965; Fama, 1970).

2.1.2 Criticism of the neoclassical approach

Although the expected utility theory has been in a central position in the study of decision-making under risky or uncertain conditions, it has been found to disregard several pervasive effects in human behavior. Individuals are often irrational in their behavior and therefore different theories of bounded rationality have been suggested by behavioralists. Kahneman and Tversky (1979) showed that in many cases, people's preferences systematically violate the axioms of the expected utility theory. They argued that people's preferences and choices are irrational and inconsistent because they depend on how those choices are presented, rather than the actual utility, cost or probability of the outcomes. For instance, people undervalue uncertain outcomes in comparison to certain outcomes. Consequently, Kahneman et al. suggested an alternative model, called prospect theory, to explain decision-making under risk.

As we have discussed above, traditional finance theory relies on the efficient market hypothesis. The theory assumes that financial markets are fundamentally rational as rational investors behave according to the expected utility hypothesis and securities trade at their fundamental value. This approach, however, is inconsistent with the reality where irrational pricing mistakes, such as bubbles and crashes, occur. The efficient market hypothesis also ignores the role of investor sentiment in the decision-making processes. Psychological phenomena can influence decision-making, and thus, financial behavior. Market trends are often caused by fluctuations in investor psychology. Since the beginning of the new millennium, there has been a wave of new research on financial markets assuming that the economic agents are less than fully rational. Thanks to cognitive psychology, economists have received extensive experimental evidence on biases, preferences and decision-making processes. According to new behavioral theories, the rationality of individuals can be compromised either in the belief-formation process or in the decision-making process. (Barberis et al., 2003: 1055–1075, 1113) Furthermore, the assumption of the efficient market hypothesis that there are no frictions in financial markets is also inconsistent with the reality. A market friction can be defined as anything that interferes with trade and such frictions do exist. Moreover, these frictions are able to interfere with investor behavior. Frictions generate costs, which in turn interfere with the decisions of rational economic agents. The capital gains tax is an obvious example of a market friction that alters investor behavior. (DeGennaro & Robotti, 2007)

It is widely accepted that investor psychology and the limits of arbitrage are the two main pillars that behavioral finance rests upon. According to the efficient market hypothesis, arbitrage brings prices to fundamental values and keeps market efficient. In reality, however, arbitrage is both risky and costly, and therefore limited. The risks and costs that result in the limits of arbitrage include the fundamental risk, noise trader risk and implementation costs, for instance. The limits of arbitrage make sure that even though some institutional investors act quite rationally and compensate for the behavior of irrational traders, they cannot completely undo the impact of irrational traders on the market. Therefore, limited arbitrage can allow substantial mispricing to occur. (Barberis et al., 2003: 1155–1165)

In traditional finance, the main pillars of asset pricing are the efficient market hypothesis, factor models (such as, capital asset pricing model), Black-Scholes option pricing model and mean-variance efficient portfolios. These theories are unable to explain everything that occurs in the real world as various predictable irrationalities have been discovered in the financial markets. These financial anomalies are inconsistent with maintained asset pricing theories and challenge the basic concepts of efficient market hypothesis and neoclassical finance. The existence of anomalies implies either market inefficiency (profit opportunities) or inadequacies in the underlying asset-pricing model. Yet, after becoming subject of academic study, these anomalies tend to disappear, reverse or attenuate. Well-known market anomalies include, for instance, various calendar effects as well as size, book-to-market, momentum and dividend yield effects. Many anomalies are potentially related to behavioral biases. Consequently, behavioral biases, heuristics and prospect theory also play a role in asset pricing in behavioral finance theory. (Shefrin, 2005: 1–12; Schwert, 2003)

2.2 Behavioral finance theory

2.2.1 Behavioral approach to rationality

Since the 1980s, an increasing number of empirical studies have begun to challenge the efficient market hypothesis. (Delcey, 2019) Behavioral theorists argue that some financial phenomena can be better explained if we abandon the idea of fully rational agents. While traditional finance theories intend to describe how investors *should* behave, behavioral theories focus on how people *actually* behave in the real world. (Baker & Nofsinger, 2002)

Behavioral economics focuses primarily on the bounded rationality of economic agents and integrates ideas from psychology, neuroscience and microeconomic theory. The concept of bounded rationality was proposed in 1982 by Herbert Simon who challenged the idea that economic agents act in a perfectly rational way. According to Simon (1982), the rationality of people is bounded because their thinking capacity, available information and time are limited. Bounded rationality has become one of the psychological foundations of behavioral economics. When explaining people's irrationality and deviation from the expected utility theory, behavioral models often need to specify where the irrationality originates. According to Barberis et al. (2003: 1055–1056), the lapse may happen either in the belief-formation or decision-making process. People may, for instance, fail to follow Bayes's law and update their beliefs according to new information received. Alternatively, people may update their beliefs correctly but, nevertheless, make normatively questionable choices that are incompatible with subjective expected utility.

The behavioral counterpart of the von Neumann-Morgenstern utility theory is known as prospect theory. It was introduced in 1979 by Kahneman and Tversky, who have had a central role in the development of the behavioral economics. Kahneman and Tversky found that, contrary to the expected utility theory, people evaluate gains, losses and different probability levels differently. In addition, they claimed that people are more concerned about potential losses than they are happy about equivalent gains. Consequently, people are willing to take more risks to avoid losses than they are to achieve gains. When offered a sure gain, most people are risk-averse and settle for the sure smaller gain, whereas if faced with sure loss, they become risk-takers. The conclusion of the theory is that people's decision-making is irrational because it depends on the context and how the choices are presented. Prospect theory has probably had more impact on finance research than any other behavioral theory. (Kahneman et al., 1979; Shefrin, 2002: 7–8; Shefrin, 2005: 2, 382)

2.2.2 Heuristics and behavioral biases

Contrary to the assumption of full rationality, investors frequently commit some common mistakes resulting from heuristics and behavioral biases. Heuristics and biases form the behavioral counterpart of the Bayesian theory. (Shefrin, 2005: 2) Heuristics can be defined as rules of thumb that people rely on to simplify the complex tasks of assessing probabilities and predicting values. Tversky and Kahneman (1974) acknowledge three types of heuristics, in particular, that are employed when making judgments under uncertainty: representativeness, availability, and adjustment from an anchor. In general, these heuristics can be useful, but sometimes they lead to biases, and severe and systematic errors. (Tversky et al., 1974) Investors can try to avoid errors and overcome behavioral biases by being aware of them and understanding the psychological processes behind them. (Baker et al., 2002)

According to Baker et al. (2002), the irrational behavior of investors can originate either from the way they think or the way they feel. For instance, the representativeness bias means that investors base their thinking on stereotypes. If a company's past stock returns have been good, investors assume that they will continue to develop the same way. Similarly, investors tend to trust more familiar companies and assess their stocks less risky than those of less well-known companies. This phenomenon is called the familiarity bias. Other examples of thought-pattern-related biases include, for instance, reference points and anchoring. These concepts refer to the habit of some investors to compare the current stock price to a fixed reference point, such as, the highest price of the previous year. In the mind of the investors, a comparison with this reference point becomes a magical dividing line which determines whether a position is at a profit or loss. (Baker et al., 2002)

In addition, investors' mood affects their level of optimism and how they analyze information. When people are in a good mood, they tend to make more optimistic judgments and less critical analyses, whereas people in a bad mood make more detailed analyses. This so-called optimism bias is also closely related to overconfidence. Investors have a tendency to be overconfident about their ability to assess stocks and available information. In addition, people tend to remember their successes while the failures are more easily forgotten, which increases their unjustified confidence. This overconfidence leads them to trade too much and take too many risks, which makes them susceptible to bigger losses. Past gains and losses can also to alter investors' risk preferences. Yet, many researchers argue that humans have a natural tendency to gamble and to take unnecessary risks. Risk-taking may be motivated by ego or entertainment. (Baker et al., 2002; Brealey, Myers & Allen 2006: 344–345.)

Furthermore, human beings are self-conscious. Therefore, they want to feel proud of their good decisions and avoid decisions that may cause regret afterwards. Investors feel proud when they sell a winning stock because it implies that they have made a good decision to buy it earlier. On the other hand, investors tend to hold on to poor-performing stocks. This predisposition to sell well-performing stocks too early and keep losing stocks too long is called disposition effect. (Baker et al., 2002)

2.2.3 Mood and decision-making

Over the past decades, many studies have examined the role that the mood and feelings play in decision-making processes. The significance of emotions in general decision-making has been studied, for instance, by Schwarz (2012) and Loewenstein et al. (2001). In addition, several studies have also focused on economic decision-making (e.g. Etzioni, 1988; Romer, 2000; Hanock, 2002; Mehra & Sah, 2002).

According to Schwarz (2012), people make mood-congruent judgments. This is seen, for instance, in the fact that people are more likely to remember certain (positive or negative) aspects of their life depending on their current state of mind (happy or sad). Schwarz has proposed feelings-as-information theory that hypothesizes that people treat their feelings as a source of information, with different types of feelings, emotions, moods and bodily sensations providing different types of information. Schwarz makes a clear distinction between emotions and moods. Since emotions arise from our appraisal of ongoing situations, they are usually rather sudden and limited in duration. They also clearly convey information about something. Meanwhile, moods can be more vague. Moods can arise gradually and last longer, and they lack a clear referent. The feelings-as-information theory assumes that changes in feelings convey more information than stable states. This can be interpreted as emotions being more informative than moods.

When people focus their attention on something, they are always experiencing some kind of feelings, either regarding the target of their focus or something else. The validity of information provided by feelings depends on whether those feelings arise from the focus of attention or from some unrelated influence. According to Schwarz (2012), people are more aware of their feelings than *where* those feelings come from. This means that people often incorrectly assume their feelings to arise from whatever happens to be the focus of their attention at the time. Consequently, they will misinterpret the information that their feelings are conveying. On the other hand, people can also attribute feelings to an incidental source, thus undermining their informational value for the task at hand. Whether people use feelings as a source of information depends on whether they rely on their informational value. In addition, people are less likely to rely on their feelings when the amount of other available information increases. (Schwarz, 2012)

Since people do not always identify the source of their feelings correctly, they are inclined to make decisions for the wrong reasons. In terms of financial decision-making, mood can have an influence on people’s expectations or risk preferences, for instance. When people are in a good mood, they tend to consider bad outcomes as less likely than if they were on bad mood. People are also more likely to resort to heuristic decision-making at the expense of analytical reasoning when they are feeling happy. (Kaustia & Rantapuska, 2015).

Furthermore, while decision-making can be influenced by mood, the mood itself can be influenced by many factors, including situational and environmental factors (Watson, 2000). Weather is one of these factors and given its important role in this study, we will discuss the psychological influences of weather in detail in the following chapter.

3 WEATHER PSYCHOLOGY

Most people believe that they are happier on a beautiful sunny day than when it is rainy and gloomy (e.g. Keller et al., 2005). However, research shows that things are not always that straightforward. In this chapter, we discuss different aspects of how weather and seasons affect people's moods and behavior. At first, we focus on the influence on moods and then move on to discuss how these moods may lead to different behavioral outcomes.

3.1 Weather and mood

3.1.1 Positive, negative or neutral effect

The majority of people believe that they are happier on sunny days as compared to dark and rainy days but research on the matter has produced mixed results. Some studies have indeed found a correlation between perceived good weather, such as high temperature, and people's high mood. To complicate the matter, other studies have, on the contrary, found high temperature to be associated with low mood, while others have found no correlation between mood and any weather variable. (Keller et al., 2005)

High mood has been found to correlate positively, for instance, with low levels of humidity (Sanders & Brizzolara, 1982), high levels of sunlight (Cunningham, 1979; Parrott & Sabini, 1990; Schwarz & Clore, 1983), high barometric pressure (Goldstein, 1972) and high temperature (Cunningham, 1979; Howarth & Hoffman, 1984). In addition, increasing number of sunshine hours has been associated with optimism, whereas long nights increase scepticism (Howarth et al., 1984). The positive impact of these weather conditions can be explained by the fact that most people consider such conditions as pleasant. Yet, defining certain type of weather as 'pleasant' is inevitably very subjective assessment with individual variation. In addition, what kind of weather conditions people are used to varies geographically and, therefore, studies conducted in different climatic zones can produce opposite results. On the other hand, Keller et al. (2005) have also discovered that nice weather can be connected to bad mood instead in the case of people who spend nearly all of their time indoors. This reverse effect could arise from people feeling resentful for not being able to enjoy the good weather.

In addition, the pleasantness of a weather condition can depend on the season. Keller et al. (2005) found that warm temperature in spring had a positive influence on people's mood when they spent a lot of time outdoors, whereas in summer, spending time out in hot weather had a negative effect on mood. Similarly, Goldstein (1972), and Howarth et al. (1984) have earlier associated high temperature with low mood and low potency, respectively.

Moreover, not only has excessively hot weather the power to decrease people's mood, but it can also increase aggression. The relationship between high temperature and increased aggressive behavior has been established by numerous studies. The positive correlation between hot weather and violence is also supported by crime statistics which reveal an increase in all sorts of criminal activities in hot weather, but in violent crimes in particular. The pattern of increasing violence with higher temperatures has also been found on a regional level. In the United States, warmer southern states have higher rates of violent crimes than northern states, despite the fact that non-violent crimes are more common in the north. The same pattern has been identified between southern and northern regions of France, Spain and Italy. It is generally believed that higher temperatures lead to increasing violence because extreme heat makes people uncomfortable and more irritable. (Harley, 2018) Yet one cannot ignore the difference in daily activities that people perform in different weather conditions and at different times of year. When people spend a lot time outside in summer, the chance of conflicts grows. (Anderson, 2001) On the other hand, a similar increase in aggression has been shown to occur also in sports as the temperatures rise (Larrick, Timmerman, Carton & Abrevaya, 2011). Since the activity remains the same (sports) but the weather conditions change, this would suggest that high temperatures can indeed have an aggression-promoting effect. By contrast, pleasant weather and the resulting good mood have been found to increase generous behavior, such as, tipping (Rind, 1996) and willingness to help (Cunningham, 1979).

However, several other studies (e.g. Watson, 2000; Keller et al., 2005; Denissen, Butalid, Penke & van Aken, 2008) have found weather to have very little, if any, effect on people's mood. Interestingly, while the weather–mood connection is often believed to be particularly strong regarding positive influence, Denissen et al. (2008) found good weather to have no positive influence on people's mood, whereas low temperature, strong wind and low levels of sunlight had a negative influence. Meanwhile, precipitation, barometric pressure and photoperiod revealed neither positive nor negative influence. However, there seems to be a great deal of individual variation in people's reactions with persons suffering from seasonal affective disorder (SAD) reacting stronger to prevailing weather conditions, including the level of sunlight, in particular.

3.1.2 Seasonal variation

When analyzing weather's influence, we should also make a distinction between daily weather changes and seasonal variation and avoid making generalizations. One of the reasons behind mixed results in studies on the association between weather and psychological changes might be the seasons. Keller et al. (2005) have argued that people react differently to beautiful weather in spring after they have been deprived of sunlight and warmth during winter months. Their study found that people spending time outdoors reacted positively to warm temperature in spring but negatively in summer, especially in regions where the temperatures rise unpleasantly high during summer months. Also other studies have found certain weather variables to have stronger influence at a particular time of the year. Denissen et al. (2008) have found wind power to have a stronger (negative) effect on mood during spring and summer. Their study did not, however, control the amount of time people spent outside so the stronger influence could be due to increased exposure.

Probably the best-known association between seasons and mood is the seasonal affective disorder. SAD is a seasonally recurrent depression that typically begins in the fall or winter and eases off in the spring as the amount of sunlight increases. Some studies claim that up to 10% of the population suffer from severe seasonal depression while most people would experience at least some degree of seasonal mood variation (Kamstra, Kramer & Levi, 2015). Consequently, the amount of suicide attempts has been shown to correlate with the season and weather conditions, both in Finland and all over the world, while the seasonality appears to become more evident the longer the distance from the equator is. In addition, whereas the suicide rate is typically highest in late spring or early summer (after months of light deprivation), the inverse correlation of the low levels of solar radiation is strongest from September to April. (Hiltunen, 2014; Ruuhela, 2018). Given the high incidence of seasonal depression, it is no wonder that there are hundreds of studies on SAD (Keller et al., 2005). Since Finland, the focus of our study, is located in high latitudes, we assume seasonal mood variation to be particularly significant there.

According to Denissen et al. (2008), some people might be more sensitive to seasonal variations of weather than others. Although their study was not able to determine the reason (personality traits, age or gender did not explain the results), there seems to be significant variation between individuals on how they react to seasonal weather variation. However, other studies have found that sensitivity to seasonal weather variation decreases with older age and that women are more likely to experience seasonal depression than men (Denissen et al., 2008). By contrast, Ruuhela's (2018) findings seem to indicate that Finnish men are more sensitive to variation in solar radiation than women.

3.1.3 Exposure and adaptation

When looking at psychological impacts of different weather conditions, we must consider one's exposure to weather. It seems logical to assume that one needs to be exposed to weather in order for it to have a psychological influence on the individual. Yet, this exposure might be insufficient or completely missing for many people, which may result in a lack of correlation between weather and mood in some studies. According to Woodcock and Custovic (1998), in industrialized countries people spend more than 90% of their time indoors on average. The Finnish Institute for Health and Welfare (2020) confirms this to be true also in Finland. On the other hand, some studies (e.g. Rind, 1996) have also found that merely being told that the weather outside is beautiful is enough to get people on high mood.

Helson's adaptation-level theory states that we must take into account that human minds evaluate differences and changes rather than absolute values. According to the adaptation-level theory, people assess different aspects of weather, such as temperature and amount of sunshine, in comparison to their past experience. They estimate whether the current weather is normal, and how big the (positive or negative) difference to a reference point is (Edwards, 2018). Due to this comparative evaluation of weather, any positive emotions springing from beautiful weather will moderate as people become accustomed to the continued exposure (Keller et al., 2005). This seems to be consistent with the feelings-as-information theory (Schwarz, 2012) that assumes that more information is conveyed by changes (in feelings) than by stable states.

On the other hand, many recent studies have linked positive feelings in the form of rising dopamine levels (dopamine is known as the feel-good neurotransmitter) to positive prediction error (Otto, Fleming & Glimcher, 2016). A prediction error occurs when there is a difference between one's expectations and the reality. This raises a question: what are people's weather expectations based on? Do they consider a weighted average of the recent past or statistically foreseeable seasonal variation? In our study, we have concluded to assess daily weather in comparison to the weather of the preceding week. How exactly we are doing this is explained in detail in Chapter 5.

3.2 Weather and cognitive abilities

Weather can also affect people's mental and physical capabilities, possibly through its influence on mood. Keller et al. (2005) found pleasant weather to be associated not only with good mood, but also with improved memory and broadened cognitive style. However, similarly to the mood-related effects that they observed, the positive influence on memory and cognition was only detected in spring. They concluded that the probable explanation for this was that people react to beautiful weather more strongly after cold and dark winter months. Furthermore, it has also been shown that good mood induced by weather conditions may improve people's emotional intelligence, problem-solving skills, and productivity in tasks requiring creativity (Lee, Gino & Staats, 2014). One study found that people perform best in a memory task at a pleasant temperature of 22 degrees Celsius, while their performance decreases with higher and lower temperatures (Keller et al., 2005). This seems to be in line with earlier findings that pleasant conditions, especially in terms of humidity, barometric pressure and temperature, improve concentration (Howarth et al., 1984).

The majority of people seem to believe that bad weather would have a negative influence on their productivity, while good weather would have a positive impact (Lee et al., 2014). According to Keller et al. (2005), bad weather and resulting negative moods may indeed impair executive functions. In addition, seasonal affective disorder has been associated with impaired memory, learning, and visual-spatial ability. In these cases, exposure to sunlight seems to have immediate alleviating effect. (Keller et al., 2005.)

However, bad weather may also increase employees' productivity if they become more motivated to stay at work in the absence of interesting outdoor activities. According to Lee et al. (2014), bad weather improves people's productivity through reduced distraction and increased focus. Their study showed that heavy rain was associated with increased speed and accuracy of participants on the task, independent of how the participants reported to feel. Similarly, a study by Sinclair, Mark and Clore (1994) suggests that on sunny and warm days people are more likely to resort to heuristic decision-making at the expense of systematic analysis than on cloudy and cool days.

3.3 Weather and economic behavior

Consumers can be affected by the projection bias, meaning that they are not able to make decisions that are the best for them in the long term. When the weather is beautiful and people feel good, they assume that those feelings persist. This is seen, for instance, in the fact that vehicle sales increase on sunny and warm days. The sales of convertible cars, in particular, increase disproportionally. Consumers tend to give excessive value to product characteristics that are useful at the time of purchase but not necessarily at other times. Consequently, four-wheel drives are sold clearly more on snowy winter days despite the fact that most people drive the same vehicle in all four seasons of the year. (Busse, Pope, Pope & Silva-Risso, 2014).

Sunlight and good weather have also been associated with increased risk-taking behavior. On beautiful days people are more likely to take risks, while bad weather increases risk aversion. (Bassi, Colacito & Fulghieri, 2012) People in a good mood are also more likely to gamble. According to Otto et al. (2016), this could be explained by the optimism bias: joyful people have unrealistically positive expectations for the future and they take more risks than when they are feeling low. Correspondingly, depressed people have been found to be more risk-averse. Individuals suffering from seasonal affective disorder exhibit greater financial risk aversion around the year than the average population. Overall, people tend to make safer financial decisions in winter than in summer. This seasonal variation in risk aversion has also influence on asset returns. In general, funds flow from risky to safe investment categories in the fall, while in the spring the flow is reversed. (Kamstra et al., 2015)

On the other hand, a study by Otto et al. (2016) has suggested that positive prediction errors could promote risk-taking regardless of the person's affective state, i.e. the mood. They found that positive and negative prediction errors related to sports and weather correlated with an increase and decrease in gambling, respectively. This suggests that unexpected good or bad weather could have a direct influence on people's risk-taking behavior without it needing to affect the person's mood necessarily. If this is true, it is especially important to examine daily weather in relation to people's expectations, and this is what we attempt to do in the empirical part of our study.

4 STUDIES ON WEATHER AND STOCK MARKET

As the field of behavioral finance has gained in importance over the past decades, the subfield that studies the effects of weather conditions on investor's behavior and consequently on stock market returns has continuously developed. The main idea behind this field of research is that weather conditions may have an impact on the mood of investors, thus influencing their risk-taking and investment behavior and consequently stock market returns. The concept of mood-induced stock return patterns is based on anomalies, which behavioral finance attempts to explain, and is therefore in opposition to the efficient market theories. Psychological studies suggest that especially ambient temperature, amount of daily sunshine and day length are prone to influence people's mood. Therefore, it is important to study the effect of these variables on investor behavior and consequently on the stock market returns. The question whether the mood of investors has any sizeable impact on stock prices or the stock market in general has raised considerable interest in finance over the past decades. In this chapter of our paper, we review the work of several authors and researchers who have studied the possible connection between different weather variables and stock market returns.

4.1 Weather and stock returns

Saunders (1993) was amongst the first researchers to connect weather conditions to investor behavior. His study was based on data from the New York area from years 1927 to 1989, and he showed that reduced cloudiness was associated with higher returns. Furthermore, the difference in returns between days with the highest cloudiness and days with the lowest cloudiness was statistically significant. The results of his study seem to confirm the general belief that sunny days make investors more optimistic and, thus, have a positive effect on stock market returns. In addition, the more pessimistic mood experienced by investors during cloudier days seems to affect the stock market negatively.

Hirshleifer and Shumway (2003) conducted a similar study as Saunders (1993) but extended the scope of the research to 26 stock market indices from 26 different countries spreading all around the world. More precisely, the authors studied the connection between the amount of sunshine in the city of the leading stock exchange in each country and the returns of those stock markets in the 26 countries between 1982 and 1997. They found that sunny days impacted stock markets positively while cloudy days had a negative effect, thus confirming the prior results obtained by Saunders. Although sunshine was found to have a strong and significant correlation with the stock market returns, rain and snow seemed to have no impact on the returns. Hirshleifer et al. point out that trading strategies based on the weather might be profitable in case of very low transaction costs. However, since the weather changes frequently, such trading strategies lead to frequent transactions and thus even small transaction costs might eliminate possible profits.

On the other hand, Coval and Moskowitz (1999, 2001), Grinblatt and Keloharju (2001), Huberman (2001) and Zhu (2002) have shown that trading has a strong local component in the sense that trading is largely concentrated amongst individuals located near a company's headquarters. Based on this and their own findings, Loughran and Schultz (2004) argue that analyzing the possible relationship of the New York Stock Exchange with the local cloudiness in New York City and the resulting mood of investors located in New York presents a crucial limitation. In fact, the movements of the NYSE are affected not only by NYC-based investors, but by investors located all around the world and subject to different weather conditions than those of NYC. Consequently, the local weather of New York City is a poor proxy for the mood of investors submitting orders to the New York Stock Exchange. In more general terms, the cloud coverage in a city of a major stock exchange is likely to be different than the cloud coverage experienced by the individuals sending orders to that exchange.

Whereas Saunders (1993) and Hirshleifer et al. (2003) analyzed the connection between stock returns and sunshine in the city of the stock exchange, Loughran et al. (2004) took a slightly different approach. To overcome the limitation that people invest disproportionally in local businesses, Loughran et al. attempted to build an alternative model of analyzing the impact of cloud cover on stock returns by using local weather data from near the headquarters of companies, as opposed to weather in the city where their stocks are traded. Using this adjusted methodology, Loughran et al. were unable to find any conclusive evidence of a connection between cloud coverage near a company's headquarters and its stock price. However, they discovered that the trading volume of companies dropped in case of a local blizzard. On the other hand, similarly to Saunders (1993) and Hirshleifer et al. (2003), Loughran et al. found weak evidence that the returns of the analyzed stocks were lower on the days that were cloudy in New York City.

Kamstra, Kramer and Levi (2003) have studied the ways seasonal affective disorder (SAD) may influence stock market returns. SAD is a major depressive disorder which may affect investors and their behavior during the seasons with fewer hours of daylight, leading to the so-called 'winter blues' effect. In their study, Kamstra et al. hypothesized that longer nights should translate into lower stock market returns. This hypothesis is based on numerous psychological studies stating that there is a clear connection between depression and lowered risk-taking behavior, which in turn lead to diminished stock returns. Kamstra et al. analyzed the movements of stock market indexes from countries at different latitudes, attempting to capture the influence of daylight on investors' mood and risk-taking behavior, and hence also on the stock returns. Based on strong evidence provided by their empirical study, Kamstra et al. concluded that there is clear connection between the seasonal cycle of stock returns and behavioral changes in investors due to seasonal affective disorder. In addition, and interestingly for our study, the authors found that countries located at higher latitudes tend to have a more pronounced SAD effect. In fact, a large and significant SAD effect was found in every northern country being part of the data sample used in the study.

However, the SAD effect and results obtained by Kamstra et al. (2003) were revisited and critically re-examined by Kelly and Meschke (2010) in their study. To do this, Kelly et al. (2010) did not only imitate Kamstra et al.'s original study containing samples from 9 countries and 12 indices, but also extended their study by analyzing data from 36 countries and 47 indices. The extensive empirical work by Kelly et al. showed that the seasonal depression observed in the population did not, in fact, match the prediction of the SAD model developed by Kamstra et al. Instead, the authors argued that the occurrence of SAD amongst the general population does not necessarily translate into a change of stock returns. Furthermore, whereas the SAD model by Kamstra et al. predicts that SAD's influence on stock markets becomes more significant the longer the distance from the equator is, Kelly et al. found no evidence to support this theory. In conclusion, the findings by Kelly et al. seem to be in complete contradiction with the previous results obtained by Kamstra et al. Moreover, there are also other studies that equally criticize Kamstra et al.'s SAD hypothesis. For instance, Goetzmann and Zhu (2005) studied investor behavior in five major American cities between January 1991 and November 1996 and found no evidence of investors being influenced by the changing number of daylight hours.

As the main aspect of their study, Cao and Wei (2005) focused on the possible relationship between temperature and stock returns on financial markets located in the United States, Canada, United Kingdom, Germany, Sweden, Australia, Japan and Taiwan during the period from 1962 to 2001. Based on evidence from psychological studies, the authors hypothesized that low temperatures lead to higher stock market returns caused by a more aggressive risk-taking behavior, whereas high temperatures could lead either to higher stock returns due to increased aggression and risk-taking or, alternatively, to lower stock returns caused by a state of apathy and a more risk-avert behavior. In their empirical analysis, Cao et al. found that temperature and stock market returns correlated negatively. The statistically significant negative correlation was observed throughout stock markets worldwide, with the strongest impact of temperature on returns occurring in Taiwan and the weakest in Australia. The results suggest that low temperatures are associated with higher returns and higher temperatures lead to reduced stock market returns. Hence, Cao et al. concluded that during summer months with higher temperatures, apathy and a reduced risk-taking behavior dominate over aggression and risk-taking, resulting in diminished stock returns.

However, besides studying the impact of temperature, Cao et al. (2005) also analyzed the possible influence of cloud coverage and SAD on the stock returns. Although cloudiness and day length appeared in general to correlate negatively with stock returns, the results were mainly statistically insignificant. It can be concluded, therefore, that the results of Cao et al. suggest that the influence of temperature on stock returns is much stronger, from a statistical point of view, than the impact of cloudiness and day length.

The impact of weather and seasonal affective disorder on various financial market segments has been studied by Frühwirth and Sögner (2015). Their results suggested that while SAD seems to have no impact on financial markets, cloud coverage has a statistically significant impact on the returns of the S&P 500 index, although the economic significance of the discovered correlation is extremely low. Nevertheless, the fact that the returns of the index seem to diminish with increasing cloudiness is consistent with the results of the above-mentioned studies by Saunders (1993) and Hirshleifer et al. (2003). On the other hand, the extremely small statistical significance of the correlation between cloud coverage and the S&P 500 index is in line with the results by Cao et al. (2005). The empirical findings of both Frühwirth et al. and Cao et al. indicate that the impact of cloud coverage on financial markets is less clear and less strong than claimed by Saunders.

The seasonality in stock markets is a well-known phenomenon that has been studied for decades and evidence of the phenomena has been found from all over the world. For instance, stock returns are typically negative in September and highly positive around new year. According to Kelly et al. (2010), this kind of seasonality of returns is in clear contradiction with the efficient market hypothesis, unless it represents pure coincidence which cannot be exploited. The seasonality of stock returns has also been discussed by Jacobsen and Marquering (2008). In their empirical study, Jacobsen et al. compared the monthly returns of the MSCI World Index between 1970 and 2004 with several weather variables observed in 48 countries. On the one hand, the authors found strong evidence of a summer–winter seasonality in the stock returns as they appeared to be significantly lower during the summer and fall months, and higher during winter and spring months. This seasonality of stock returns was indeed observed in various countries. On the other hand, Jacobsen et al. claim that there is not enough empirical evidence available to connect temperature and other weather variables directly to stock market returns through a change in the behavior and mood of investors. More precisely, they interpret their results to show no evidence of investors suffering from seasonal affective disorder or being affected by thermal changes. Therefore, the authors state that it is premature to assume that the observed summer–winter seasonality of the market returns is caused by behavioral changes of investors resulting from changing weather conditions. The conclusion of their study is that even if a connection between some weather-related variables and stock returns is observed, this correlation might in fact result from other seasonal phenomena, such as the Halloween effect, and therefore drawing a conclusion that weather affects stock returns through changes in mood is premature.

On the other hand, other studies have looked at how weather-related mood factors impact financial market activities overall, not just in the form of stock returns. For instance, Lu and Chou (2012) have analyzed the relationship between weather and the Shanghai Stock Exchange. They point out that most studies focus on the correlation between weather conditions and stock prices in developed capital markets that are quote-driven. However, the trading behavior and price formation mechanism on Chinese stock exchanges differs a lot from those in well-developed capital markets. Since Chinese stock exchanges were established later, a fully electronic order-driven trading mechanism was put into place. Therefore, the authors study whether the weather-related correlation is also valid in emerging capital markets and particularly in those that are order-driven, such as the Shanghai Stock Exchange (SSE). On the other hand, the sale and purchase orders of the SSE are entered into the system by brokers located all over China. Therefore, Lu et al. argue that analyzing the impact of the local weather in Shanghai on the SSE is not sufficient, but one should take into account the weather conditions in the entire country. This would be extremely complicated, however.

Apart from analyzing the connection between the local weather and stock prices, Lu et al. (2012) also studied the impact of the weather on market liquidity, volatility or other trading variables of the SSE. Several interesting findings were made. Firstly, the authors show that although only around a third of all the orders to the Shanghai Stock Exchange come from the Shanghai area, the weather in and around Shanghai has an impact on the Shanghai Composite Index. In addition, the strength of the impact was found to vary depending on the time of day. However, the results indicate that in general weather's influence on the returns is extremely small and insignificant, unless the weather conditions are extreme and exceptional, such as, heavy rain and snowfall. By contrast, the authors found that the weather in Shanghai had a significant impact on various trading activities, such as turnover, volatility and liquidity. Their results show that heavy cloud coverage and SAD effect tend to reduce trading activities significantly, whereas during longer periods of sunshine investors appear to be more inclined to participate in trading activities. In addition, temperature, barometric pressure and wind were found to have significant positive effects on turnover and volatility. However, whereas cloudiness reduced both turnover and volatility, SAD did not seem to affect volatility.

The varying intensity of weather's influence on stock returns has also been discovered by Chang, Chen, Chou and Lin (2008). In their paper, they analyzed the connection between weather in New York City and the returns and trading patterns of New York Stock Exchange. Their results suggest that cloud cover has a negative impact on stock prices, but only at the opening of the market. Therefore, it can be concluded that the direct impacts of weather on returns are not uniform throughout the day but are likely to be concentrated in specific periods of the day. By contrast, cloudiness generally seems to lead to reduced volatility and reduced market depth during the entire trading day. Symeonidis, Daskalakis and Markellos (2010) are in the same lines with Chang et al. in this. In their paper, Symeonidis et al. conclude that cloudiness and SAD are negatively associated with volatility of stock markets. The results of their study show that implied volatility indices for the Chicago Board Options Exchange (CBOE) and realized S&P 500 index returns are inversely correlated with cloudiness and the number of nighttime hours. The findings of both of these studies suggest that weather conditions can have a significant impact on the trading behavior. Furthermore, they are in line with view that good mood leads to increased trading activity and higher volatility.

Dowling and Lucey (2008) have completed a comprehensive study analyzing the possible impact of investor's mood on global equity prices and return variance. In their paper, they used a diverse and global equity dataset regrouping 37 national indices and 21 national small capitalization indices. To determine the mood of investors, the authors used several mood proxy variables, such as, the amount of rain, temperature, windspeed and seasonal affective disorder. The main conclusion of their study was that SAD appears to be the most robust mood proxy, showing a statistically significant correlation with both the equity returns and variance. Furthermore, the SAD effect was found to be stronger on small capitalization indices than on the main national indices and to become increasingly significant the further a country is from the equator. In addition, Dowling et al. suggest the different weather variables have only very small, if any, influence on equity returns and return variance. They did, however, identify a possible positive correlation between low temperatures and equity returns, and between rain and variance.

The impact of wind on stock markets has been studied for instance by Keef and Roush (2002). They analyzed how the wind speed and direction influence stock returns in New Zealand. The wind conditions were observed in Wellington, the capital city of New Zealand. The results of their analysis show that both increased windspeed and wind coming from the south have a statistically significant negative impact on the returns of the stock exchange. In other words, the higher the wind speed, the lower the stock returns. These findings are consistent with the geographic location of New Zealand where the south wind comes in fact from the Antarctic Continent. Therefore, south wind is extremely cold and results in reduced investor sentiment.

Silva and Almeida (2011) have studied the impact of four weather variables on the returns of the Portuguese Stock Index (PSI-Geral). The variables included in the study were rain, temperature, sunshine and windspeed, and the analyzed time period was from January 2000 to December 2009. Their results revealed a certain influence of the temperature variable on the returns of the index as especially low temperatures seemed to be associated with higher returns. The authors suggest that this could be due to low temperatures increasing aggressiveness and risk-taking behavior of investors. In addition, low levels of sunshine and persistent bad weather seemed to be associated with higher returns in the study. However, Silva et al. state that low temperatures, lack of sunshine and persistent bad weather are typical winter characteristics and, therefore, their positive correlation with returns might, in fact, be a result of seasonal patterns of the stock market.

4.2 Weather and the Helsinki Stock Exchange

In the following, we are going to discuss a study conducted by Kaustia and Rantapuska (2015) who have attempted to capture the mood changes of investors by using local weather data and hours of daylight. Although their extensive research focused on trading behavior rather than on stock returns, their results are of great interest to us because the study focuses solely on Finnish trading. While we analyze on the possible effect of eight weather parameters on the returns of the OMX Helsinki Price Index, Kaustia et al. have studied the influence of the temperature, precipitation, sunniness and the length of days on the trading behavior of Finnish investors. The authors argue that statistical correlation between environmental mood parameters and stock returns can occur for multiple reasons and, therefore, their goal is to examine the direct link between investors' mood and trading actions instead. Kaustia et al.'s paper represents the first analysis of the hypothesis that mood influences the behavior of investors in Finland. To conduct their study, the authors used daily trading records and transaction data from all investors in the country during a period from 1995 to 2002. They hypothesize that people on good mood are more optimistic with an increased level of risk tolerance and, consequently, people are more likely to buy stocks on longer and sunnier days. In addition, Finnish investors are divided into three categories in the study: individuals, financial corporations and non-financial corporations. The daily buy ratio is analyzed separately for each investor group as well as for each municipality in Finland.

Kaustia et al. (2015) found that sunshine, temperature and precipitation often have the correct sign to align with their hypothesis. For instance, their results show that when weather changes from full cloud cover to blue skies, the buy ratio increases by 1.7% for financial institutions, 0.9% for non-financial corporations, and 0.2% for individual investors. However, the impact of temperature and sunny weather on the trading behavior appears to be statistically insignificant. On the other hand, the level of precipitation is negatively correlated with the buy ratio of all three investor groups and is statistically significant at the 1% level for individual investors and at the 5% level for financial institutions. The estimated coefficients for the effect of precipitation imply that on a day when it rains 10 millimeters above the average amount of rain of a rainy day, the buy ratio of individual investors drops to 1.9% below the daily average. For financial corporations, the impact is even stronger with the buy ratio 3.8% below the daily average. However, Kaustia et al. conclude that, based on their overall findings, weather-induced daily variation in mood does not appear to have any major impact on the trading behavior of Finnish investors.

However, Kaustia et al. (2015) studied also how the changing length of day impacts the trading behavior of investors. The SAD hypothesis assumes that a reduced level of exposure to daylight generates a higher risk aversion and an increased amount of stock sales. Thus, investors living in northern areas with shorter days should be more prone to selling stocks in comparison to investors living in Southern Finland. Yet, Kaustia et al.'s results reveal that investors tend to trade less during longer days and that individuals based in the northern part of Finland tend to buy more stocks during the darkest months of the year. The negative correlation between the trading volume and length of day is contrary to the SAD hypothesis and highlights the presence of seasonal trading patterns. The data shows that Finnish investors tend to trade less during holiday months as compared to the rest of the year. In addition, one would expect that investors suffering from SAD would become apathic and, therefore, trade less in the fall season, but there is no evidence of this in the data.

Lastly, Kaustia et al. (2015) analyzed the presence of different seasonal patterns in the Finnish stock market. They found conclusive evidence that domestic individual investors tend to sell more stocks during the spring and summer period from May to July, whereas from August to October these individual investors seem to purchase rather than sell. The trading behavior of individual investors coincides rather well with the holiday seasons in Finland. Thus, it seems that Finnish investors liquidate stocks prior and during their summer and Christmas holidays and repurchase stocks right after those holiday periods have ended. In addition, the trading volume decreases significantly in case of both individual investors and corporations between May and August, with a period of complete drought in July which is the most popular vacation month in Finland.

To summarize, Kaustia et al. (2015) do not find conclusive evidence that weather-induced mood changes would effectively impact the trading behavior of Finnish investors. The signs of both sunshine and temperature coefficients are in line with their hypothesis, but the results are statistically insignificant. Instead, precipitation has the strongest correlation with investors' trading behavior and is also statistically significant. Overall, the magnitude of the weather effect on trading behavior is very small on a population level. Thus, the authors conclude that, from a point of view of economic significance, daily mood changes appear to have no significant influence on people's investing decisions. Furthermore, they find no evidence that SAD influences the tendency to buy or sell stocks, whereas it does influence the trading volume. Finally, the clear seasonal patterns visible in the Finnish stock market data do not seem to be caused by weather-induced mood changes, but rather align with the Finnish holiday seasons.

4.3 Critical viewpoint

Although there are numerous studies supporting the hypothesis that weather can impact stock prices and trading activity, many academics have begun to question the plausibility of the reported statistical significance in some of these original studies. Over the years, more and more studies are raising concerns that the statistically significant correlation between weather and stock returns is indeed a result of data mining or spurious correlation. (Kim, 2017) A spurious correlation, i.e. correlation between variables without a causal relationship, can occur due to either coincidence or the presence of some unseen parameter. Thus, a spurious correlation gives misleading statistical evidence regarding a potential linear relation between variables. Loughran et al. (2004), who found weak evidence that the returns of NYSE correlate with cloudiness in New York City, were along the same lines when concluding that they "would not dismiss the possibility that the relationship between cloud cover in New York and stock returns is spurious". Furthermore, Jacobsen et al. (2008) have also argued that the influence of the weather observed in their study may be a consequence of data-driven inference based on spurious correlation. They also showed that the seasonal anomaly in stock returns is likely to be caused by other factors than weather-induced changes in the mood of investors.

Saunders' (1993) study, which highlighted weather's statistically significant effect on stock returns, is one of those which has received a great deal of criticism. Krämer and Runde (1997) attempted to replicate Saunders' results by analyzing German weather and stock returns and stated that statistical significance of the weather variables on the stock returns depends mainly on how the null hypothesis is phrased. Meanwhile, Trombley (1997) has claimed that Saunders' results depend largely on the type of return and the sample period analyzed. On the other hand, Gigerenzer (2004) has argued that a small p-value leading to a statistical significance has little scientific value if obtained due to a large sample size. Similarly, Wasserstein and Lazar (2016) refer in their paper to a statement issued by the American Statistical Association (ASA) expressing concerns regarding the unappropriated use of the p-value criteria. The ASA cautions against an improper use to the p-value criteria that falsifies scientific analysis and invalidates numerous scientific results. The ASA states that even the tiniest effects can produce a small p-value in case of a high enough sample size, and warns that "widespread use of statistical significance as a license for making a claim of a scientific finding leads to considerable distortion of the scientific process". (Wasserstein et al., 2016).

Kim's (2017) study is the first to review in detail the statistical problems in the research model used in the earlier studies, particularly in the studies by Saunders (1993) and Hirshleifer et al. (2003). According to Kim, the studies by Saunders and Hirshleifer et al. have resulted in spurious statistical significance because of using too large data samples. In his research, Kim highlights that an unbiased research model requires a sample size of no more than 2,000 observations. To prove his point, Kim re-examines the statistical significance reported in the two studies by using different methods: the Bayesian method and adaptive level of significance by Perez and Perichhi (2014). These methods represent alternatives to the p-value criteria adopted in prior studies. According to Kim's empirical study, neither the Bayesian method nor the adaptive level of significance support the hypothesis that weather impacts stock returns as claimed by Hirshleifer et al. and Saunders. Furthermore, Kim conducted additional experiments in order to prove that even parameters with no economic relevance can be shown to be statistically significant if inappropriate statistical tools are applied. He studied the effect of the number of sunspots on stock returns while applying the same statistical process as used in Hirshleifer et al.'s study. Kim's results show that the number of sunspots, a variable with no economic significance, has a statistically significant impact on stock returns due to a simple data mining process, that is, increasing the sample size until statistical significance is achieved at a conventional level. Based on his empirical experiments, Kim concluded that the statistically significant impact of the weather on stock returns reported in many studies has a high probability of being a spurious correlation. Meanwhile, the two alternative methods to the p-value criteria suggested by Kim provide strong support for the null hypothesis, implying that the weather has no significant effect on the stock returns. Although the null hypothesis is often violated in reality, the deviation is economically negligible.

However, when the sample size grows, the likelihood of rejecting the true null hypothesis becomes very high. Kim (2017) shows that with the statistical model and data employed by Hirshleifer et al. (2003), a sample size of 2,000 to 4,000 observations results in the statistical power being below 0.4, which implies only weak statistical evidence. Yet, when the sample size is increased to 40,000 observations, the statistical power reaches 1. This shows that Hirshleifer et al.'s study with a sample size of 92,808 is clearly flawed at the 5% significance level. In conclusion, if the sample size is very large, the significance level should be considerably reduced in order to avoid Type I errors, that is, the rejection of the null hypothesis even when there is no real correlation.

Furthermore, Kim (2017) found that a number of previous studies on the impact of weather on stock returns have extremely small values for R^2. In fact, a clear majority of studies had R^2 values below 0.05 which implies that the statistical models studying the correlation between weather and stock returns can only explain less than 5% of the overall variation of the stock returns. Similarly, Loughran et al. (2004) report very low R^2 values in their study on the impact of cloudiness on stock returns. Out of their 25 regressions, the highest adjusted R^2 value is 0.003, indicating that little to none of the variation of the returns can actually be explained by the cloudiness. Moreover, Kim (2017) found that there is in fact a negative correlation between the sample size and R^2 values. In other words, a larger sample of observations does not enhance the quality of the statistical model, but only inflates the value of the test statistic. This constitutes additional evidence that employing as many observations as many previous studies have done is not statistically sound but results in data mining.

Dyckman and Zeff (2014) and Ioannidis and Doucouliagos (2013) have argued that an appropriate selection of sample size and significance level are key factors to improve the credibility of research. Nevertheless, the research design used by Hirshleifer et al. (2003) appears to be widely adopted in the studies on weather's influence on stock returns. For example, Kamstra et al. (2003) have used up to 19,000 observations to analyze the influence of the seasonal depression on stock returns. They reached statistical significance at a conventional level of significance (5%) combined with extremely small R^2 values. While most studies use p-values less than 0.05 as a main criterion for statistical significance, the ASA states that "scientific conclusions […] should not be based only on whether a p-value passes a certain threshold" (Wasserstein et al., 2016). Similarly, Kim (2017) argues that due to the massive size of observations used in the previous studies, the level of significance used in combination with the p-value criteria should be lowered considerably.

4.4 Summary of previous research

In conclusion, the previous research that we have examined has produced mixed answers to the question whether weather or seasonal affective disorder can affect stock returns indirectly by influencing the mood of investors. Many studies have reported statistically significant correlations between weather variables and stock returns and used this anomaly as evidence of inefficient markets. For instance, Kamstra et al. (2003) and Dowling et al. (2008) have argued that the SAD effect can have a negative influence on stock returns during winter months. In addition, Cao et al. (2005) found a negative correlation between day length and returns at an insignificant level. On the other hand, Lu et al. (2012) and Symeonidis et al. (2010) have suggested that the SAD effect could affect trading behavior even if it did not influence the returns. Meanwhile, Kelly et al. (2010), Goetzmann et al. (2005) and Frühwirth et al. (2015) refute the idea that day length would influence stock returns through the SAD effect.

Out of different weather variables, particularly cloudiness and temperature have been of interest in many studies. Two of the studies that we have looked at, namely those by Saunders (1993) and Hirshleifer et al. (2003), suggest a strong negative correlation between cloudiness and stock returns. However, weak or temporally limited negative correlation has also been found by Loughran et al. (2004), Cao et al. (2005), Frühwirth et al. (2015) and Chang et al. (2008). Furthermore, Chang et al. (2008), Symeonidis et al. (2010) and Lu et al. (2012) have shown cloudiness to influence trading behavior in a way that translates into changes in market turnover, volatility and market depth. Meanwhile, the results concerning temperature are not as convincing. Jacobsen et al. (2008) and Silva et al. (2011) found temperature to correlate negatively with returns but concluded that this connection is likely to be related to seasonal patterns of stock markets. In addition, Dowling et al. (2008) reported a possible weak link between temperature and stock returns. On the other hand, the results by Cao et al. (2005) provide strong evidence that temperature correlates negatively with returns. The authors explain this by higher temperatures causing apathy and reduced risk-taking behavior. In addition, Lu et al. (2012) suggest that temperature to influences trading behavior in form of higher temperatures increasing turnover and volatility.

On the other hand, there is not much empirical evidence that, for instance, rain would affect stock returns. Kaustia et al. (2015), who did not look at returns, found that rainfall has a negative impact on the buy ratio in the Finnish stock market. Meanwhile, Hirshleifer et al. (2003), Goetzmann et al. (2005) and Dowling et al. (2008) have concluded that rain does not influence stock returns, and Lu et al. (2012) have argued that only extreme rainfall can have an effect. In fact, Lu et al. suggest that even though various weather conditions influence trading activities in general, only extreme weather can influence returns. Jacobsen et al. (2008) and Silva et al. (2011) also avoid concluding that weather conditions affect stock returns. Although both studies discovered certain weather variables to correlate with returns, they caution against making hasty conclusions as unrelated seasonal phenomena might be to blame.

Meanwhile, Kim (2017) goes further in his argumentation against the weather effect by claiming that much of the previous evidence in favor of the hypothesis have been achieved by using faulty methodology. According to Kim (2017), the combination of a large sample size and the use of the p-value criteria as basis for the significance tests has strong potential for spurious and artificial statistical significance. This issue has also been raised by Krämer et al. (1997), Trombley (1997), Loughran et al. (2004), and Jacobsen et al. (2008). Furthermore, the American Statistical Association has also given a clear warning that the inappropriate use of statistical methods impacts the validity and distort scientific findings. Yet, this research model in favor of large sample sizes and the p-value criteria has been used by Saunders (1993), Hirshleifer et al. (2003) and many other authors. Dyckman et al. (2014), Ioannidis et al. (2013) and Kim (2017) have argued that if large sample sizes are used, the applied level of significance must be adjusted accordingly. Otherwise, any statistical analysis is seriously biased against the null hypothesis and, thus, wrongfully favors the hypothesis that the weather has an impact on the stock returns. As an alternative to using the p-value criteria for the analysis of statistical significance, Kim has suggested the Bayes factor or the adaptive level of significance. In fact, when re-examining the studies by Saunders (1993) and Hirshleifer et al. (2003) using these alternative methods, Kim found strong evidence supporting the null hypothesis and, thus, refuting the idea that the weather has any significant impact on stock returns.

5 DATA AND METHODOLOGY

In this chapter, we introduce the financial and weather data analyzed in the study and explain the methodology that we use to conduct the analysis. A time period of 20 years, from January 1, 2000 to December 31, 2019, is used for the analysis with the exception of weekend days. Weekends are excluded from the analysis since stocks do not trade on weekends. Holidays have not excluded since national Finnish holidays do not always coincide with international holidays. This leaves us with 5,216 observation days.

5.1 Stock market data

In this study, we analyze the influence of weather conditions on the Helsinki Stock Exchange. For that purpose, we are using the OMX Helsinki Price Index (OMXHPI) which is the general index containing all the stocks listed in the Helsinki Stock Exchange. The index data has been obtained using Thomson Reuters Datastream which is a time series data retrieval service.

In addition, we use the STOXX Europe 600 as an independent variable. The STOXX Europe 600 is a stock index of European stocks. The index has a fixed number of 600 components representing large, mid and small capitalization companies from 17 European countries. The index is widely diversified geographically including stocks traded around the whole continental Europe and in the United Kingdom. Therefore, there cannot be any correlation between the return of the STOXX Europe 600 index and weather conditions in Finland.

Furthermore, the 3-month Euribor interest rate has been used to calculate the rate of return of both the OMX Helsinki and STOXX Europe 600 indexes. 'Euribor' stands for Euro Interbank Offered Rate. The Euribor rates are the most important reference rates in the European money market. The rates are based on the average interest rates at which a large panel of European banks borrow funds from each other.

All the financial variables are listed in Table 1 shown on the following page. Information about the value ranges and standard deviations of each variable is also included.

TABLE 1. Financial variables

FINANCIAL VARIABLES				
Variable	Average	Max.	Min.	Standard deviation
OMXHPI	8069.41	18331.02	4110.31	2336.93
STOXX600	307.79	419.74	157.97	62.36
Euribor3M	1.71	5.47	-0.45	1.79

5.2 Weather data

The weather data for this study is mostly provided by the Finnish Meteorological Institute. We have chosen to use eight different weather variables both as absolute values and as relative values that are compared to a reference point. Five of the weather variables used in the analysis were readily available for download on the website of the Finnish Meteorological Institute (2020), while three other variables have been calculated by us based on available data.

The five readily available weather variables provided by the Finnish Meteorological Institute and used in our analysis are: daily precipitation, daily thickness of the snow cover (snow depth), daily average temperature, daily maximum temperature and daily minimum temperature. The measurements have been observed in Kaisaniemi weather station which is the closest weather station to the Helsinki Stock Exchange providing extensive weather data. In addition, we wanted to include in our analysis three other weather variables for which the Finnish Meteorological Institute did not provide *daily* values. However, the Institute's data download includes so-called 'instantaneous observations'. These are weather observations that are recorded once in every ten minutes or one hour, so we have used this data to calculate additional variables. The instantaneous observations include, for instance, hourly-measured cloud cover data expressed as a number from 0 to 8, where 0 means 'clear skies' and 8 means 'very cloudy'. Based on the hourly measurements, we have calculated an average daily cloud cover for each day of the observation period.

Furthermore, we wanted to include a sunshine variable that is affected both by the daily cloud cover and by the seasonal variation in sunshine. The Finnish Meteorological Institute gathers diverse radiation data observed once in every minute, ten minutes or one hour. We decided to use hourly-measured global radiation data to calculate a daily solar radiation value. 'Global radiation' refers to direct shortwave solar radiation and diffuse radiation (scattered radiation through the clouds and other particles in the atmosphere) reaching the Earth's surface. The amount of global radiation is expressed as watts per meter². The value calculated by us does not represent the total amount of daily global radiation because the values measured by the Institute at each full hour do not represent the total hourly radiation but the amount of radiation at that specific moment. Nevertheless, the daily global radiation value that we have calculated can still give us an indication of how sunny a particular day was in comparison to other days.

Additionally, since it is well-established that the number of daylight hours can have a great impact on human mood and even lead to seasonal affective disorder, we decided to use the length of day as one variable along with the traditional weather data. We assume that in a northern country like Finland, the impact of daylight hours might be very significant. However, the Finnish Meteorological Institute does not publish statistics on day length. Instead, Moisio (2020) provides downloadable data on the time of sunrise and sunset in Helsinki for any given day. We used these times to calculate the length of each day from 2000 to 2019.

Table 2 below summarizes all eight daily weather variables that we have used in the analysis. The units of measurement, average values, range of variation and standard deviations are also depicted. The minimum value for snow depth seen in the table is -1 (cm). This is the minimum measurement used by the Finnish Meteorological Institute to indicate that there is no snow near the weather station. Meanwhile, '0' would mean there is no snow on the exact spot of measurement but there is snow somewhere nearby.

TABLE 2. Daily weather variables

ABSOLUTE DAILY VALUES				
Variable	Average	Max.	Min.	Standard deviation
Precipitation (mm)	1.8	52.0	0.0	4.2
Snow depth (cm)	4.6	73.0	-1	12.3
Av. Temperature (°C)	6.7	26.4	-22.7	8.6
Max. temperature (°C)	9.8	30.4	-20.9	9.1
Min. temperature (°C)	3.8	22.5	-27.0	8.5
Global radiation (watt/m^2)	2666	8749	9	2422
Cloud cover (0–8)	4.6	8	0	2.5
Day length (h)	12.4	18.9	5.8	4.4

Since Helson's adaptation-level theory argues that people are more likely to evaluate weather conditions in relation to past weather and changes occurred rather than as unconnected absolute values (Edwards, 2018), we want to take this into account in our analysis. In addition, many studies have shown that especially *unexpected* positive outcomes (including changes in weather), have a clear impact on people's mood and risk-taking behavior (Otto et al., 2016). Logically, a certain weather condition is most likely to be unexpected when it differs significantly from past weather. Therefore, rather than just analyzing the influence of the above-mentioned eight weather variables on stock returns as absolute daily values, we also analyze the influence of the same weather parameters when they are compared to a reference point.

To do this, we compare each daily value to a weekly average value that we have calculated based on the daily values of the preceding seven days. For instance, if it has not rained at all during seven consecutive days (0 mm a day on average), but it rains 10 mm on Day 8, the relative rain value of Day 8 is +10 mm. Then again, if it has rained on average 5 mm a day during the previous week but not at all on Day 8, the relative rain value of Day 8 is -5 mm (while the absolute daily rain value is 0 mm). With this method, we have calculated a relative value for each weather parameter and each observation day. In the following, we call them "weekly difference" values as they illustrate the difference of the daily weather to average weekly weather (weather of the previous seven days). Table 3 below illustrates the weekly difference variables and their descriptive statistics.

TABLE 3. Weekly difference weather variables

WEEKLY DIFFERENCE VALUES				
Variable	Average	Max.	Min.	Standard deviation
Precipitation (mm)	–	+50.6	-16.9	4.3
Snow depth (cm)	–	+31.0	-17.7	3.2
Av. Temperature (°C)	–	+16.0	-17.7	3.2
Max. temperature (°C)	–	+16.3	-17.9	3.2
Min. temperature (°C)	–	+17.9	-16.7	3.7
Global radiation (watt/m²)	–	+4690	-6642	1286
Cloud cover (0–8)	–	+7.0	-7.2	2.2
Day length (h)	–	+0.09	-0.09	0.08

It is worth noting that, unlike in case of most daily weather variables, the minimum value for all weekly difference variables can fall below zero. In other words, although the amount of rain, snow cover, solar radiation, cloud cover or day length cannot be negative in absolute terms, their daily value can be lower than the preceding week's average value. Consequently, the relative weekly difference value can be negative. On the other hand, the average value of the weekly difference variables is in practice always zero and, therefore, they are excluded from Table 3.

Additionally, we also experimented with a daily reference point, that is, comparing the absolute value of each day to the previous day's value, but the weekly reference point seemed to yield better results with our data. This seems logical since people's memory of the past weather extends further than just yesterday. On the other hand, Otto et al. (2016) also suggest that people's weather expectations might be based on foreseeable seasonal variation. In addition, previous studies have shown significant seasonal shifts in investors' risk preferences (e.g. Kamstra et al., 2015). Analyzing the influence of weather on stock returns with the help of seasonal reference points is outside the scope of this study but might provide an interesting area for future research.

5.3 Methodology

The empirical part of this study is conducted using Ordinary Least Squares (OLS) regression. OLS regression is a statistical method of analysis that estimates the relationship between a dependent variable and one or more independent variables. The dependent variable in this study is the OMX Helsinki Price Index and there are two sets of independent variables: the STOXX Europe 600 Index and the daily weather data comprised of several weather variables.

We use a combined weather variable test to determine the influence of all the different weather variables on the stock prices. In addition, we run additional tests in which we leave out individual variables one by one until only the significant variables are left. We also perform a robustness check in order to analyze whether the Monday/Friday effect plays a role in the variation of the OMXHPI returns.

As mentioned before, we have chosen a time period of 20 years for our analysis. Figure 1 below illustrates the history of the OMX Helsinki Price Index during the full time period from 2000 to 2019.

FIGURE 1. OMX Helsinki PI from 2000 to 2019 (Nasdaq Nordic, 2020).

In addition to analyzing the full time period from 2000 to 2019, we run the tests for four shorter time periods. The five time periods analyzed are:

- full time period: January 3, 2000 to December 31, 2019,
- before the subprime crisis: January 3, 2000 to July 17, 2007,
- during the subprime crisis: July 17, 2007 to March 9, 2009,
- after the subprime crisis: March 9, 2009 to December 31, 2019, and
- negative interest rate period: April 28, 2015 to December 31, 2019.

The reason for analyzing these periods separately is that we assume that the investor behavior might have varied during different economic periods. In addition, using these smaller sample sizes improves the reliability of our results as the likelihood of spurious correlation is reduced. Kim (2017) has suggested that sample sizes should include no more than 2,000 observations or the used significance level should be adjusted. While our full time period includes 5,216 observations, the periods before the subprime crisis (1,966 observations), during the subprime crisis (430), after the subprime crisis (2,822) and during the negative interest rate (1,221) have significantly smaller number of observations and are mostly in line with Kim's suggestion.

Our analysis has been conducted using the following regression equation:

$$r_t = \alpha + \beta_1 \text{ PRECIPITATION}_t + \beta_2 \text{ SNOW}_t + \beta_3 \text{ AV TEMPERATURE}_t + \beta_4 \text{ MAX TEMPERATURE}_t + \beta_5 \text{ MIN TEMPERATURE}_t + \beta_6 \text{ RADIATION}_t + \beta_7 \text{ CLOUD}_t + \beta_8 \text{ DAY LENGTH}_t + \varepsilon_t$$

In addition, we have used in total seven different reduced equations that include only statistically significant variables. We have obtained these reduced equations by running the tests for each time period first with the full equation and then eliminating the least significant variables out of the equation one by one, until we have been left with only those variables that are significant during that particular time period. The different reduced equations are presented later in Tables 5 and 7 which also show which time period each equation has been used for.

6 RESULTS AND ANALYSIS

The aim of our analysis is to establish whether there is some statistically significant correlation between the OMX Helsinki Price Index and one or more weather variables. In other words, we try to determine if the movement of the index can be partly explained by changes in the local weather. Since weather conditions have been shown to impact the mood of individuals and, mood in turn influences optimism and risk preferences, we expect to see small correlation between some of the weather variables and stock returns. In particular, we expect high levels of sunshine (measured as global radiation in this study) to have a positive impact on the mood of investors. However, it is possible that the influence on stock returns is not observed when absolute daily values are used due to seasonal patterns of stock market having the opposite effect. Therefore, the positive influence of sunshine might become visible when it analyzed in comparison to a weekly reference point (weekly difference value of global radiation in this study). Similarly, we would expect shorter days (low values in length of day in our study) to have a negative effect on the returns through the SAD effect, but this connection might also be hidden by un-weather-related seasonal variation. By contrast, we assume that high levels of cloudiness have a negative impact on the stock market independent of the season. Again, the impact might be more apparent when analyzing the weekly difference values. In addition, we would intuitively like to assume that rain has a negative impact on the returns although previous research does not support this view. On the other hand, the perceived pleasantness of (high and low) temperatures depends highly on the individual and season, and hence, we expect the relationship between temperature, mood and stock market to be more complex and unpredictable.

As explained in Chapter 5, our study covers eight different weather parameters. In our regression analysis, they are used both as absolute daily values and as relative weekly difference values. The equation also includes the STOXX 600 index as an independent variable since the OMX Helsinki index is highly correlated with the movements of the STOXX 600. In addition, we have added a variable that tests if the Monday anomaly is present in the movement of the index. Furthermore, besides analyzing the entire period of 2000–2019, we have divided the analysis into four additional time periods, namely, prior to the subprime crisis, during the subprime crisis, after the subprime crisis, and during the negative interest rate period. We assume that the behavior of investors might change depending on the economic environment and, therefore, the movement of the OMX index could show a different level of correlation with weather depending on the time period analyzed.

The following Table 4 highlights the results of our regression analysis of the relationship between the daily returns of the OMX Helsinki index and different weather variables, measured as absolute daily values. As can be seen from the table, we have done two separate regression tests for each time period. Firstly, we have analyzed all the weather variables at the same time, and secondly, we have reduced the equation by leaving out the least significant variables one by one until we were left with only statistically significant variables. Table 5 below shows the basic (full) regression equation that we have used, as well as the various reduced equations (with only significant variables) that we have applied for different time periods. The results of both full and reduced equation analyses for each period can be seen in Table 4. Like the table shows, none of the weather variables were significant during the subprime crisis when we applied the full equation, nor became significant through the process of eliminating the least significant variables. Therefore, no reduced equation has been used in the analysis of that particular time period with absolute daily values.

Meanwhile, the following Table 6 presents the results of our regression analysis when the relative weekly difference values are applied. With the weekly difference values, we find statistically significant variables in every time period. The reduced equations used with the relative values can be seen in Table 7. Next, we move on to summarize and interpret the results presented in Tables 4 and 6. We will do this by focusing on one weather variable at the time. The absolute and relative values of each weather variable are discussed simultaneously.

TABLE 4. Influence of daily weather variables on OMXHPI

ABSOLUTE DAILY VALUES										
Variable	Full time period		Prior subprime crisis		During subprime crisis		After subprime crisis		Negative interest rate period	
	Full equation	Reduced equation	Full equation	Reduced equation	Full equation	Reduced equation	Full equation	Reduced equation	Full equation	Reduced equation
Constant	0.0114	-0.0680	-0.1343	-0.2637*	0.1568		0.0663	0.0992**	0.0573	0.0274*
Stoxx600	1.0854***	1.0847***	1.3085***	1.3078***	0.9382***		0.9754***	0.9759***	0.8525***	0.8542***
Monday	0.0193		0.0290		0.0581		0.0127		0.0206	
Precipitation	-0.0007		0.0087		-0.0060		-0.0055*	-0.0051*	-0.0115**	-0.0110**
Snow depth	0.0000		-0.0030		0.0005		0.0012		0.0013	
Av. temperature	0.0149		0.0622		-0.0141		-0.0129		-0.0018	
Max. temperature	-0.0098		-0.0350		0.0038		0.0057		-0.0034	
Min. temperature	-0.0035		-0.0294		0.0168		0.0115	0.0033*	0.0083	
Global radiation	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001		0.0000		0.0000	
Cloud cover	-0.0140		-0.0317		-0.0443		0.0058		0.0064	
Day length	0.0156	0.0127*	0.0539**	0.0433**	0.0129		-0.0100	-0.0084**	-0.0077	

TABLE 5. Regression equations used with absolute daily values

REGRESSION EQUATIONS FOR DAILY VALUES		
	Regression equation	Used for
1	$r_t = \alpha + \beta_1$ PRECIPITATION$_t$ + β_2 SNOW$_t$ + β_3 AV TEMPERATURE$_t$ + β_4 MAX TEMPERATURE$_t$ + β_5 MIN TEMPERATURE$_t$ + β_6 RADIATION$_t$ + β_7 CLOUD$_t$ + β_8 DAY LENGTH$_t$ + ε_t	Full time period, Prior subprime crisis, During subprime crisis After subprime crisis, Negative interest rate period
2	$r_t = \alpha + \beta_1$ RADIATION$_t$ + β_2 DAY LENTH$_t$ + ε_t	Full time period, Prior subprime crisis
3	$r_t = \alpha + \beta_1$ PRECIPITATION$_t$ + β_2 MIN TEMPERATURE$_t$ + β_3 DAY LENGHT$_t$ + ε_t	After subprime crisis
4	$r_t = \alpha + \beta_1$ PRECIPITATION$_t$ + ε_t	Negative interest rate period

TABLE 6. Influence of weekly weather difference on OMXHPI

WEEKLY DIFFERENCE VALUES										
Variable	Full time period		Prior subprime crisis		During subprime crisis		After subprime crisis		Negative interest rate period	
	Full equation	Reduced equation	Full equation	Reduced equation	Full equation	Reduced equation	Full equation	Reduced equation	Full equation	Reduced equation
Constant	-0.0144	-0.0105	-0.0194	-0.0158	-0.0595	-0.0426	-0.0047	-0.0023	0.0018	0.0065
Stoxx600	1.0858***	1.0859***	1.3079***	1.3078***	0.9374***	0.9377***	0.9756***	0.9756***	0.8532***	0.8544***
Monday	0.0194		0.0269		0.0562		0.0124		0.0225	
Precipitation	-0.0018		0.0046		-0.0055		-0.0055		-0.0106*	-0.0109**
Snow depth	0.0032		0.0021		0.0052		0.0064*	0.0066*	0.0120*	0.0112*
Av. temperature	0.0050		0.0399		-0.0298		-0.0140		0.0089	
Max. temperature	-0.0042		-0.0162		-0.0160		0.0052		-0.0120	
Min. temperature	-0.0021		-0.0277		0.0333		0.0125	0.0051*	0.0060	
Global radiation	-0.0001**	-0.0001***	-0.0001**	-0.0001**	-0.0001	-0.0001*	0.0000		0.0000	
Cloud cover	-0.0185*	-0.0194*	-0.0329		-0.0414	-0.0454*	0.0046		-0.0039	
Day length	-0.1975		-0.3071		-0.2033		-0.0969		-0.0186	

TABLE 7. Regression equations used with relative weekly difference values

REGRESSION EQUATIONS FOR WEEKLY DIFFERENCE VALUES		
	Regression equation	Used for
1	$r_t = \alpha + \beta_1$ PRECIPITATION$_t$ + β_2 SNOW$_t$ + β_3 AV TEMPERATURE$_t$ + β_4 MAX TEMPERATURE$_t$ + β_5 MIN TEMPERATURE$_t$ + β_6 RADIATION$_t$ + β_7 CLOUD$_t$ + β_8 DAY LENGTH$_t$ + ε_t	Full time period, Prior subprime crisis, During subprime crisis After subprime crisis, Negative interest rate period
2	$r_t = \alpha + \beta_1$ RADIATION$_t$ + β_2 CLOUD$_t$ + ε_t	Full time period, During subprime crisis
3	$r_t = \alpha + \beta_1$ RADIATION$_t$ + ε_t	Prior subprime crisis
4	$r_t = \alpha + \beta_1$ SNOW$_t$ + β_3 MIN TEMPERATURE$_t$ + ε_t	After subprime crisis
5	$r_t = \alpha + \beta_1$ PRECIPITATION$_t$ + β_2 SNOW$_t$ + ε_t	Negative interest rate period

6.1 Precipitation

The results of our regression analysis show that the total amount of daily rain correlates negatively with stock returns during four out of the five time periods analyzed. However, the correlation is statistically significant only during two of the time periods, namely, after the subprime crisis (at the 10% significance level) and during the negative interest rate period (at the 5% level). Secondly, the negative correlation is also visible during the same four time periods when the regressions are run with the weekly difference variables. Negative correlation with the relative weekly difference variables would suggest that when an individual day is rainier than the preceding seven days on average, it has a negative impact on the stock market. Alternatively, the indication might also be that the market picks up when the skies clear up after a rainy week. Yet, in this case, the relation is statistically significant only during one of the time periods: at the 5% level during the negative interest rate period.

The results obtained with absolute values and relative values both suggest negative correlation at a similar level of significance. Although inconclusive, the results seem to comply with our expectation that rain can have a negative impact on mood and on stock returns. The effect seems to ensue both from daily rain as an isolated event and from increased raininess in relative terms. On the other hand, negative correlation with the weekly difference variables might also suggest that the absence of rain after a rainy period has a positive impact on the market.

6.2 Snow depth

We did not find much psychological literature discussing the influence of snow on mood and, therefore, we are forced to formulate different hypotheses. It is difficult, however, to try to assess the psychological impact of snow without a seasonal dimension. For many people, snow is an intrinsic part of winter, especially around Christmas time, and glistening white snow can also ease the gloominess of winter months. In these cases, deep snow cover could be associated with high mood. But, if snow cover is associated with positive emotions, how should our analysis observe the fact that people are often thought to be on better mood in summer (with an obvious absence of snow)? On the other hand, in spring and fall snow can be an indication of unseasonably cold temperatures which could be associated with low mood. Furthermore, melting snow can also turn into slush which, in most cases, has a negative influence on mood.

Perhaps for these reasons, our analysis of the absolute daily values for snow depth produces inconclusive results. We discovered positive, but statistically insignificant, correlation between snow cover and stock returns during four out of the five time periods. The lack of seasonal dimension in our analysis also means that the quality of snow (which affects people's attitudes towards the snow) is not taken into account in any way. In other words, when analyzing snow depth in absolute terms (using daily values), 5 centimeters of melting slushy snow are seen equal to 5 centimeters of fresh dry snow. However, analyzing snow depth in relative terms allows at least partial observation of seasonality. When the analysis is conducted with relative weekly difference values, melting snow is associated with a negative value and fresh new snow with a positive value. In addition, in the weekly difference analysis, the value '0' is more likely to be associated with stable snow-free seasons, whereas with the daily values, '0' (and in some cases also '-1') is often associated with unstable weather with temperatures around zero degrees Celsius.

Indeed, the analysis of the relative weekly values yields better results and reveals a positive correlation during all of the analyzed time periods. In addition, during two of the time periods, namely after the subprime crisis and during the negative interest rate period, we find the positive correlation to be significant at the 10% level. Positive correlation of the relative snow depth suggests either that increasing amount of snow has a positive impact on the stocks or, alternatively, that melting snow cover has a negative impact. These results are in clear contrast with our findings related to precipitation. While precipitation seems to correlate negatively with stock returns, the influence of snow seems to be positive. However, the discovered relationship is statistically significant only with relative values (i.e. increasing or decreasing amounts of snow) and during two of the time periods.

6.3 Average temperature

Our regression analysis reveals no clear relation between daily average temperature and stock returns either with absolute values or with relative weekly difference values. In the analysis of the daily values, the coefficient for average temperature variable is negative for three out of five time periods, whereas with weekly difference values, the coefficient is negative only for two of the time periods. Moreover, none the regression coefficients are statistically significant.

As explained before, the relationship between the temperature and mood is highly seasonal, and dependent on individual preferences. The regression equation used in the analysis does not take into account seasonal variation in temperature. Hence, our inconclusive results do not come as a surprise. On the other hand, using weekly difference values levels out the seasonal variation because relative values only tell if a particular day has been warmer or colder than the preceding week on average. Thus, we could have expected to see some indication of people's preference (most probably) toward warm weather in relative terms, i.e. toward positive weekly difference values. Even though other studies have observed that high temperatures tend to have a negative influence on mood, we suppose that in the temperate climate of Finland people would instead react positively to warmer temperatures. Yet, our results did not reveal any preference to either direction.

6.4 Maximum temperature

We find the coefficient for maximum temperature to be negative for three out of the five time periods with absolute daily values, and for four out of the five time periods with relative weekly difference values. Although the negative sign of the coefficient seems to be fairly consistent, it does not suggest statistically significant correlation. Moreover, an actual negative impact of higher temperatures on stock returns would be somewhat unexpected. If real, the negative impact of high absolute values in maximum temperature could indicate that in summer temperatures can rise too high also in a northern country like Finland. Alternatively, the observed negative correlation might result from positive impact of low maximum temperatures in winter. One explanation for this could be that people are happy when low temperatures allow snow to stay on the ground longer. Yet, when other studies have produced similar results, the authors have often interpreted them to arise from unrelated seasonal patterns. Low temperatures happen to coincide with winter months when stock returns tend to be higher.

6.5 Minimum temperature

Our analysis of the daily minimum temperature's influence on stock market also comes back inconclusive. The daily values and weekly difference values both show a positive correlation in three out of the five time periods, namely during the subprime crisis, after the subprime crisis and during the negative interest period. Meanwhile, the coefficient for the two other time periods is negative at an insignificant level. However, for the period after the subprime crisis the positive correlation seems to be significant at the 10% level with both datasets. Yet, the 10% significance level is only achieved with the reduced equation (i.e. equation including only significant variables). Meanwhile, with the full equation no statistically significant correlation is found. The results seem to suggest that daily minimum temperature (both in absolute and relative terms) does not influence stock returns.

6.6 Global radiation

The results of our regression analysis clearly show that the amount of global radiation correlates negatively with stock returns. We find the coefficient to be negative for three out of the five time periods analyzed, while for the two other time periods the coefficient is zero. The correlation is consistently negative both with absolute daily values and relative weekly difference values. Furthermore, most of the negative coefficients are statistically significant. With the daily values, the coefficients are significant at the 1% level both for the full time period and for the period before the subprime crisis. Meanwhile, with the weekly difference values, we find significance for the same time periods at the 1% and 5% levels, respectively.

The negative correlation of the absolute values suggest that high levels of sunshine could have negative influence on stock returns, whereas low levels of sunshine are associated with increased returns. This finding is unexpected since it is contrary to our hypothesis which assumes that high levels of sunshine are associated with high mood and increased stock returns. Since high levels of sunshine are measured primarily during summer months and low levels are observed during winter, one explanation for this unexpected correlation could be the so-called Halloween effect which refers to a seasonal pattern where stock returns tend to be significantly lower during a period from May to September/October than during the remainder of the year. Although most anomalies disappear or fade after being recorded, Bouman and Jacobsen (2002) have shown the Halloween effect to hold true in most countries over a period of several decades. The results of Kaustia et al. (2015) also show that Finnish stock market follows this pattern mostly, although the authors also connect it to the Finnish holiday seasons. Therefore, it is most likely that our results reveal typical seasonal variation in the Finnish stock market, rather than a negative influence of solar radiation on stock returns.

By contrast, the relative weekly difference values eliminate the seasonal variation in solar radiation and focus on daily variation. Therefore, with the weekly difference values, both ends of the scale are primarily occupied by summer days. This is because large amounts of daily radiation allow large variation. In other words, large positive values indicate a significant increase in sunshine in comparison to the past week, whereas large negative values mean a significant decrease in sunshine. Yet, although the relativity of weekly difference values rules out the Halloween effect, the amount of global radiation correlates negatively with stock returns on a statistically significant level. This would suggest that the market is negatively influenced whenever an individual day is sunnier than the previous week, and vice versa. This is surprising and contrary to all our expectations. However, the coefficients are extremely small (-0.0001), indicating that the negative influence of global radiation is very mild.

6.7 Cloud cover

The coefficients of the cloud cover are predominantly negative, suggesting a negative correlation between the cloud cover and stock returns. With the absolute values, the negative sign is present during three out of the five time periods, whereas with relative values the coefficient is negative in four out of five cases. However, the negative correlation is statistically significant (at the 10% level) only with the weekly difference values and during two time periods, namely the full time period and during the subprime crisis. The negative correlation of the relative values implies that when a day is cloudier than the preceding week on average, the stock returns are negatively affected, or alternatively, when a day is less cloudy than the previous week on average, the stock returns are positively affected. These findings seem to confirm our expectations related to cloudiness. They are, however, in contradiction with our previous results regarding the influence of global radiation. On the other hand, the negative correlation of global radiation could be explained by unrelated seasonal patterns, which we have discussed above, and therefore it does not invalidate our findings related to cloudiness.

6.8 Day length

First, it is worth clarifying what the daily values and weekly difference values mean in relation to day length. The daily values tell us the length of day in hours. Hence, the absolute day length values are largest during the summer solstice and smallest during the winter solstice. The relative values, instead, indicate if days are getting longer (spring) or shorter (fall). However, days begin to shorten immediately after the summer solstice (when the length of day is nearly 19 hours) and lengthen immediately after the winter solstice (length of day is less than 6 hours). Consequently, the weekly difference values of day length are always positive during the time period from winter solstice to summer solstice (approx. December 21 to June 21) and negative from summer solstice to winter solstice (approx. June 21 to December 21). The change in day length around the solstices is approximately 10 minutes on a weekly level and therefore barely noticeable by human perception. We do not expect people's mood to be affected by such minuscule changes, but instead, general attitudes toward different seasons could play some role. For instance, spring season might make people happy simply because they know that the amount of daylight is increasing.

Analyzing the influence of day length on stock returns in absolute terms produces mixed results. We find a positive coefficient during three out of the five time periods analyzed, while a negative sign is found during the two remaining periods. Moreover, the positive correlation is statistically significant during the full time period and prior to the subprime crisis, at the 10% and 5% levels, respectively. Yet, the negative correlation after the subprime crisis is also significant at the 5% level. And what is more, during the exact same two time periods when longer days (summer) show a significant positive correlation with stock returns, we have previously found that high levels of solar radiation (sunny summer days) correlate negatively with returns, also at a significant level.

Using weekly difference values in the equation produces more consistent results. We find the coefficient of the day length to be negative during all five time periods. Negative correlation of the relative values would suggest that stock returns go down in spring (or more precisely, from December to June) and rise in fall (from June to December). However, the correlation is not significant at a statistical level during any of the time periods.

6.9 Discussion

Previous studies have produced mixed results concerning the possible relationship between weather conditions and stock returns. Other studies seem to confirm that at least some weather variables can influence returns, while others either fail to find any correlation or doubt their implications. In our empirical study, we have identified significant correlation of some weather variables, although none of the variables showed consistent correlation at a statistically significant level during all of the analyzed time periods. In addition, the possible economic impact suggested by these correlations seems to be very small. Moreover, we also need to question whether the correlations implicate a causal relation or arise from unrelated seasonal variation of stock returns.

The statistically significant correlations were, for the most part, evenly divided into one or two variables per analyzed time period with both absolute and relative values. There were two exceptions to this pattern: three significant daily weather variables were identified in the period after the subprime crisis, whereas no significant daily variables were found in the subprime crisis period. Thus, we cannot confirm that a larger number of observations during certain periods (full time period, and after the subprime crisis) would have produced clearly more significant results like has been suggested by Kim (2017). Nevertheless, it is worth keeping in mind that the reliability of the results obtained for the shorter time periods (before the subprime crisis, during the subprime crisis, and during the negative interest rate period) is better than for the periods including more than 2,000 observations.

Previous studies have suggested that rainfall has no influence on stock returns (Hirshleifer et al., 2003; Goetzmann et al., 2005; Dowling et al., 2008) unless it is extreme (Lu et al., 2012). Yet, we discovered that precipitation in Helsinki has a fairly consistent negative correlation with the returns of the OMX Helsinki index. This correlation was significant during some of the time periods that we analyzed. In addition, the inverse correlation was discovered both with the absolute and relative values, indicating that dry weather after a rainy period could have a positive impact on returns. Although our results seem to be in contradiction with previous findings about rain and stock returns, Kaustia et al. (2015) have previously suggested that rainfall could indeed affect the mood of Finnish investors negatively and, thus, also influence their trading behavior to some extent.

The influence of snow on stock returns has not been studied much. The few studies that we found discussing snow focused on snowfall as an exceptional event. Lu et al. (2012) found that unusual snowfall in Shanghai affected negatively the returns of the local stock exchange, whereas Loughran et al. (2004) did not identify any connection between snowfall and stock returns but showed, instead, that a blizzard in a company's hometown causes a drop in the trading volume of its stocks. However, in Finland snowfall is far from unusual, and the weather variable included in our data was, in fact, snow depth. We discovered that the variable for snow depth was mostly positively correlated with the returns of the OMX Helsinki, with the relative weekly difference values being significant during two time periods. Since we found no psychological studies on the impact of snow cover on mood, we were forced to interpret our results according to our own assumptions. In addition, we assumed that the weekly difference values can be used partly to assess the quality of snow. Consequently, since increasing snow depth was positively correlated with stock returns, we hypothesized that this is because increasing snow often means dry fresh snow that improves people's mood. On the other hand, we assumed that decreasing snow depth translates into slushy snow that has a negative impact on mood and, thus, on stock returns.

Previous studies on the relationship between temperature and stock returns have suggested that if there is any link between the two, it is that low temperatures increase stock returns (Jacobsen et al., 2008; Silva et al., 2011; Dowling et al., 2008). Yet, many authors point out that low temperatures coincide with winter months when stock returns tend to be higher. On the other hand, Cao et al. (2005) have also argued that high temperatures in summer cause apathy in investors which leads to decreased returns. Our analysis of relationship between the three temperature variables and the OMX Helsinki reveals no clear correlation, indicating that temperature does not influence the index. Since the Finnish climate is temperate, we expected to see some indication of investors' preference toward increasing temperatures (positive weekly difference values), but our results did not reveal any preference.

Sunshine and cloudiness have often been analyzed together in previous studies. Several studies have found cloudiness to be either strongly (Saunders, 1993; Hirshleifer et al., 2003) or weakly (Loughran et al., 2004; Cao et al., 2005; Frühwirth et al., 2015; Chang et al., 2008) associated with declined stock returns. By contrast, Silva et al. (2011) discovered that intense sunshine correlated negatively with returns whereas low levels of sunshine had a positive effect. However, the authors pointed out that the correlation might result from seasonal patterns of stock market. Our results also suggest that cloudiness is negatively correlated with the returns of the OMX Helsinki index, particularly in terms of relative cloudiness measured with the weekly difference values. This finding is, however, in contradiction with the results of our analysis on the influence of global radiation. We found that high and increased levels of global radiation have a consistent and significant negative correlation with the returns of the OMX Helsinki. As high absolute values are associated with summer months, we can assume, similarly to previous studies, that the negative correlation is due to seasonal variation or the Halloween effect. Yet, the negative correlation of relative weekly difference values implies that stock prices are negatively influenced when an individual day is sunnier than the preceding week, and vice versa. This unexpected result is in contradiction to previous findings by both us and other researchers who suggest that cloudiness has a negative influence on returns. However, although the negative correlation of global radiation is statistically significant during several of the analyzed time periods, the coefficients are extremely small and, thus, the possible impact on returns is negligible.

Researchers are divided on whether the number of daylight hours can have an impact on stock returns through seasonal affective disorder (SAD) influencing investors' mood and behavior. Kamstra et al. (2003) and Dowling et al. (2008), for instance, are in favor of this view and argue that the SAD effect pushes stock returns down in winter. Several other authors claim that day length has no influence on returns (Kelly et al., 2010; Goetzmann et al., 2005; Frühwirth et al., 2015), while some admit that it can nonetheless affect trading behavior (Lu et al., 2012; Symeonidis et al., 2010). Our analysis of the matter produces very mixed results. When we analyzed the influence of day length in absolute terms, we found statistically significant coefficients for different time periods with both positive and negative signs. Thus, no conclusions could be drawn on whether day length in absolute terms has any impact on the OMX Helsinki index. On the other hand, the positive and negative values of relative day length present, in fact, half-year periods between the summer and winter solstice. Therefore, the consistent negative correlation of the weekly difference values suggests a seasonal pattern in the returns of OMX Helsinki: a decline from December to June and a rise from June to December. This approximate timeline aligns partly with the seasonal patterns of the Finnish stock market detailed by Kaustia et al. (2015). However, the correlations are statistically insignificant. Thus, we must conclude that our analysis does not provide evidence of day length or SAD effect influencing the returns of the OMX Helsinki index.

7 CONCLUSIONS

In this study, we have analyzed the influence of local weather on the Helsinki Stock Exchange. Using OLS regression method, we have tried to establish whether there is some statistically significant correlation between the OMX Helsinki Price Index and one or more weather variables. Our analysis covered in total eight weather parameters: precipitation, snow depth, average temperature, maximum temperature, minimum temperature, global radiation, cloud cover and day length. In addition to looking at the weather of each day independently, we have also analyzed it relatively, in the context of the preceding week. This viewpoint was included because of Helson's adaptation-level theory which states that individuals become adapted to continued conditions and therefore react more strongly to changing circumstances.

We analyzed the returns of the OMX Helsinki Price Index during a period of 20 years from January 1, 2000 to December 31, 2019. In addition to analyzing the full time period, we divided it into four shorter periods: prior to the subprime crisis, during the subprime crisis, after the subprime crisis and during the negative interest rate period. Furthermore, because the OMX Helsinki is highly correlated with the movements of the STOXX Europe 600 index, we used the STOXX index as an independent variable. The returns of the STOXX Europe 600 cannot be influenced by local weather in Helsinki since the index is widely diversified geographically, including stocks traded all around Europe.

Our analysis did not give a conclusive answer to whether the returns of the OMX Helsinki Price Index are influenced by the daily weather. We found some correlation with both the absolute daily weather variables and relative weekly difference variables but neither of the datasets indicates a consistent statistically significant correlation with the stock returns. Our most promising findings were the negative correlation of precipitation both in absolute and relative terms, the negative correlation of relative cloudiness, and the positive correlation of relative snow cover. Our results suggesting negative influence of cloudiness on stock returns are in line with previous research, whereas the negative correlation of precipitation observed by us is in contradiction with several earlier studies that concluded that normal amounts of rainfall have no impact on returns. The influence of snow depth on stock returns has not been studied before, which makes our finding about its positive influence even more interesting. Yet, a higher level of significance and more consistent occurrence across the analyzed time periods would be necessary for all of these three variables in order to draw definite conclusions. Moreover, we found that the significant coefficients were relatively small, indicating that the possible economic impact of these weather variables on the OMX Helsinki index is very mild.

Meanwhile, the global radiation variable was found to have highly significant coefficients, all negative, both with the daily and weekly difference values. We concluded, however, that the reason why high levels of solar radiation in absolute terms correlate negatively with the returns is because stocks tend to go down in summer. Thus, there is no causal relation between high levels of sunshine and decreased returns. By contrast, the negative correlation of the relative amount of sunshine is more difficult to explain but, on the other hand, the coefficients are so tiny that the impact on the returns is negligible.

Although our results do not confirm our initial hypothesis that the Helsinki Stock Exchange is influenced by the local weather, they do not provide conclusive evidence in favor of the null hypothesis either. It is possible that improved methodology or different weather data would yield more conclusive results. For instance, we have used variables that measure the weather of an entire day. Since stock markets trade only during working hours, it might produce better results to use weather data only from those hours. Furthermore, studies have shown that weather's influence on stock returns varies even during a trading day (Lu et al., 2012; Chang et al., 2008). In addition, while conducting our analysis, we noticed that our model failed to take sufficient account of seasonal variation in weather. The perception of pleasant weather varies depending on the season. Temperature that is deemed pleasantly warm in spring might be considered too cold in summer. Precipitation is often unwelcomed in summer whereas in winter people might be happy to have fresh snow. Although using weekly difference values reduced the significance of seasonal variation to some extent, further research should include an improved model that gives an adequate consideration to the seasonal dimension in the complex ways how weather influences mood. Additionally, further study could also include an analysis of whether certain weather variables impact the volatility of the index.

On the other hand, it is also possible that our hypothesis is false and the movements of the OMX Helsinki index are completely independent from local weather conditions. This could be because Finnish investors are unaffected by weather conditions for some reason. In our analysis, we have used weather data from Helsinki, but it is possible that the investors are not located in Helsinki but elsewhere in Finland or even abroad. According to Kaustia et al. (2015), foreign investors constitute approximately 45 per cent of the trading volume of the Helsinki Stock Exchange. Therefore, the local weather in Helsinki does not necessarily have any influence on the investors' mood or behavior. On the other hand, some studies (e.g. Lu et al., 2012; Symeonidis et al., 2010) have shown that even if weather had an impact on investors' trading behavior, this impact did not necessarily transfer to stock prices.

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APPENDICES

APPENDIX 1 Rats code

```
allocate 5217
OPEN DATA Data 2000-2019.xlsx
CALENDAR(d) 2000:01:03
DATA(FORMAT=XLSX,ORG=COLUMNS) / Euribor3M OMXH STOXX600E
Rainfall Snow Temp TempH TempL TempDiff Daylenght Radiation Cloud

set OMX = 100.00*log(OMXH/OMXH{1})-EURIBOR3M/360.00
set STOXX = 100.00*log(STOXX600E/STOXX600E{1})-Euribor3M/360.00
set Monday = %if(%weekday(t)==1,1.00,0.00)
set Friday = Monday{4}

display "The whole sample"

linreg(robust) OMX / resid
# constant stoxx TempH Snow Rainfall Monday Tempdiff daylenght Radiation
Cloud

Display "Prior the Subprime crisis"

linreg(robust) OMX 1 2007:07:17 resid
# constant stoxx TempH Snow Rainfall Monday Tempdiff daylenght Radiation
Cloud

display "After the Subprime crisis"

linreg(robust) OMX 2009:03:09 5217 resid
# constant stoxx TempH Snow Rainfall Monday Tempdiff daylenght Radiation
Cloud

display "Negative Interest rate period"

linreg(robust) OMX 2015:04:28 5217 resid
# constant stoxx TempH Snow Rainfall Monday Tempdiff daylenght Radiation
Cloud

display "During the Subprime crisis"

linreg(robust) OMX 2007:07:17 2009:03:09 resid
# constant stoxx TempH Snow Rainfall Monday Tempdiff daylenght Radiation
Cloud
```

APPENDIX 2 Linear regression of daily values - full equation

Full equation with dependent variable OMX and all independent weather variables measured as absolute daily values

Full time period (daily data from 04/01/2000 to 31/12/2019)

Usable Observations	5216
Centered R^2	0.5798067
R-Bar^2	0.5789994
Uncentered R^2	0.5798325
Mean of Dependent Variable	-0.013184275
Std Error of Dependent Variable	1.683920823
Standard Error of Estimate	1.092604559
Sum of Squared Residuals	6213.6494783
Durbin-Watson Statistic	2.0761

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	0.011442532	0.094612954	0.12094	0.90373822
2. STOXX	1.085426152	0.020871762	52.00453	0.00000000
3. TEMPH	-0.009816747	0.015070658	-0.65138	0.51480026
4. TEMPL	-0.003478618	0.010280304	-0.33838	0.73507917
5. TEMP	0.014930472	0.020848234	0.71615	0.47389845
6. SNOW	-0.000048923	0.001172893	-0.04171	0.96672876
7. RAINFALL	-0.000709634	0.004055186	-0.17499	0.86108415
8. MONDAY	0.019336691	0.032111197	0.60218	0.54705494
9. DAYLENGHT	0.015604732	0.009759752	1.59889	0.10984590
10. RADIATION	-0.000053847	0.000019740	-2.72779	0.00637609
11. CLOUD	-0.014010914	0.010026541	-1.39738	0.16229857

Prior the subprime crisis (daily data from 03/01/2000 to 17/07/2007)

Usable Observations	1966
Centered R^2	0.4984076
R-Bar^2	0.4958419
Uncentered R^2	0.4984634
Mean of Dependent Variable	-0.022490220
Std Error of Dependent Variable	2.132904070
Standard Error of Estimate	1.514449145
Sum of Squared Residuals	4483.9023937
Durbin-Watson Statistic	2.0610

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	-0.134340569	0.200114429	-0.67132	0.50201749
2. STOXX	1.308458076	0.046476612	28.15304	0.00000000
3. TEMPH	-0.034980452	0.030619458	-1.14243	0.25327717
4. TEMPL	-0.029369958	0.020535660	-1.43019	0.15266164
5. TEMP	0.062190555	0.042459908	1.46469	0.14300582
6. SNOW	-0.002966523	0.003963841	-0.74840	0.45422129
7. RAINFALL	0.008706755	0.009524251	0.91417	0.36062914
8. MONDAY	0.029034198	0.069279772	0.41909	0.67515312
9. DAYLENGHT	0.053865555	0.022207602	2.42555	0.01528539
10. RADIATION	-0.000141589	0.000045707	-3.09777	0.00194980
11. CLOUD	-0.031651011	0.021515302	-1.47109	0.14126596

<u>During the subprime crisis</u> (daily data from 17/07/2007 to 09/03/2009)

Usable Observations	430
Centered R^2	0.7973512
R-Bar^2	0.7925147
Uncentered R^2	0.8003235
Mean of Dependent Variable	-0.255862675
Std Error of Dependent Variable	2.099555909
Standard Error of Estimate	0.956359441
Sum of Squared Residuals	383.22719630
Durbin-Watson Statistic	2.0662

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	0.156812162	0.256683330	0.61092	0.54125465
2. STOXX	0.938226187	0.031322091	29.95414	0.00000000
3. TEMPH	0.003794141	0.051447468	0.07375	0.94121102
4. TEMPL	0.016846818	0.046462042	0.36259	0.71690883
5. TEMP	-0.014051625	0.081516476	-0.17238	0.86314058
6. SNOW	0.000546901	0.010193316	0.05365	0.95721170
7. RAINFALL	-0.006042447	0.012376000	-0.48824	0.62538051
8. MONDAY	0.058115510	0.107695451	0.53963	0.58945341
9. DAYLENGHT	0.012865605	0.026028424	0.49429	0.62110096
10. RADIATION	-0.000065205	0.000056571	-1.15262	0.24906806
11. CLOUD	-0.044315000	0.032593149	-1.35964	0.17394339

<u>After the subprime crisis</u> (daily data from 09/03/2009 to 31/12/2019)

Usable Observations	2822
Centered R^2	0.7162314
R-Bar^2	0.7152219
Uncentered R^2	0.7164190
Mean of Dependent Variable	0.0303406404
Std Error of Dependent Variable	1.1798477716
Standard Error of Estimate	0.6296210697
Sum of Squared Residuals	1114.3441854
Durbin-Watson Statistic	2.1727

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	0.066346269	0.074932915	0.88541	0.37593614
2. STOXX	0.975398137	0.022900026	42.59376	0.00000000
3. TEMPH	0.005698312	0.010973917	0.51926	0.60357973
4. TEMPL	0.011475567	0.008649526	1.32673	0.18459873
5. TEMP	-0.012902499	0.015999601	-0.80643	0.41999709
6. SNOW	0.001177298	0.000961213	1.22480	0.22064906
7. RAINFALL	-0.005534383	0.003446470	-1.60581	0.09931523
8. MONDAY	0.012749386	0.028898375	0.44118	0.65908267
9. DAYLENGHT	-0.010008120	0.006676403	-1.49903	0.13386618
10. RADIATION	0.000006277	0.000013576	0.46233	0.64384194
11. CLOUD	0.005793054	0.007574439	0.76482	0.44438094

Negative interest rate period (daily data from 28/04/2015 to 31/12/2019)

Usable Observations	1221
Centered R^2	0.6919171
R-Bar^2	0.6893709
Uncentered R^2	0.6919370
Mean of Dependent Variable	0.0078213684
Std Error of Dependent Variable	0.9732742419
Standard Error of Estimate	0.5424457121
Sum of Squared Residuals	356.03929420
Durbin-Watson Statistic	2.2761

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	0.057323648	0.112827873	0.50806	0.61140928
2. STOXX	0.852536433	0.047281137	18.03122	0.00000000
3. TEMPH	-0.003360966	0.015198120	-0.22114	0.82498068
4. TEMPL	0.008344195	0.013357663	0.62467	0.53218457
5. TEMP	-0.001821489	0.022468329	-0.08107	0.93538694
6. SNOW	0.001289871	0.002729749	0.47252	0.63655291
7. RAINFALL	-0.011484864	0.005565244	-2.06368	0.03904838
8. MONDAY	0.020594382	0.037897722	0.54342	0.58684062
9. DAYLENGHT	-0.007658588	0.009006528	-0.85034	0.39513750
10. RADIATION	0.000015165	0.000017498	0.86671	0.38609926
11. CLOUD	0.006366075	0.010386195	0.61294	0.53991849

APPENDIX 3 Linear regression of daily values - reduced equation

Reduced equation with dependent variable OMX and only statistically significant independent weather variables measured as absolute daily values

Full time period (daily data from 04/1/2000 to 31/12/2019)

Usable Observations	5216
Centered R^2	0.5795734
R-Bar^2	0.5793314
Uncentered R^2	0.5795991
Mean of Dependent Variable	-0.013184275
Std Error of Dependent Variable	1.683920823
Standard Error of Estimate	1.092173754
Sum of Squared Residuals	6217.1003722
Durbin-Watson Statistic	2.0745

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	-0.067973319	0.063308991	-1.07368	0.28296810
2. STOXX	1.084712878	0.020810126	52.12428	0.00000000
3. DAYLENGHT	0.012719542	0.007660941	1.66031	0.09685198
4. RADIATION	-0.000037353	0.000014000	-2.66817	0.00762659

Prior the subprime crisis (daily data from 03/01/2000 to 17/07/2007)

Usable Observations	1966
Centered R^2	0.4971624
R-Bar^2	0.4963935
Uncentered R^2	0.4972183
Mean of Dependent Variable	-0.022490220
Std Error of Dependent Variable	2.132904070
Standard Error of Estimate	1.513620390
Sum of Squared Residuals	4495.0335952
Durbin-Watson Statistic	2.0582

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	-0.263732901	0.142057280	-1.85653	0.06337875
2. STOXX	1.307803525	0.046463067	28.14716	0.00000000
3. DAYLENGHT	0.043252597	0.017571594	2.46151	0.01383548
4. RADIATION	-0.000106745	0.000032889	-3.24565	0.00117182

After the subprime crisis (daily data from 09/03/2009 to 31/12/2019)

Usable Observations	2822
Centered R^2	0.7159388
R-Bar^2	0.7155355
Uncentered R^2	0.7161266
Mean of Dependent Variable	0.0303406404
Std Error of Dependent Variable	1.1798477716
Standard Error of Estimate	0.6292743748
Sum of Squared Residuals	1115.4932347
Durbin-Watson Statistic	2.1720

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	0.099244910	0.042166553	2.35364	0.01859058
2. STOXX	0.975896723	0.022861175	42.68795	0.00000000
3. TEMPL	0.003284385	0.001937156	1.69547	0.08998672
4. RAINFALL	-0.005122212	0.003337328	-1.53482	0.09982694
5. DAYLENGHT	-0.008424715	0.003746888	-2.24846	0.02454709

Negative interest rate period (daily data from 28/04/2015 to 31/12/2019)

Usable Observations	1221
Centered R^2	0.6911731
R-Bar^2	0.6906660
Uncentered R^2	0.6911931
Mean of Dependent Variable	0.0078213684
Std Error of Dependent Variable	0.9732742419
Standard Error of Estimate	0.5413137400
Sum of Squared Residuals	356.89904835
Durbin-Watson Statistic	2.2772

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	0.027394884	0.016425772	1.66780	0.09535566
2. STOXX	0.854173720	0.047756498	17.88602	0.00000000
3. RAINFALL	-0.011030372	0.005522885	-1.99721	0.04580215

APPENDIX 4 Linear regression of weekly values – full equation

Full equation with dependent variable OMX and all independent weather variables measured as relative weekly difference values

Full time period (daily data from 04/01/2000:01 to 31/12/2019)

Usable Observations	5216
Centered R^2	0.5796774
R-Bar^2	0.5788698
Uncentered R^2	0.5797031
Mean of Dependent Variable	-0.013184275
Std Error of Dependent Variable	1.683920823
Standard Error of Estimate	1.092772707
Sum of Squared Residuals	6215.5621482
Durbin-Watson Statistic	2.0765

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	-0.014374662	0.017687274	-0.81271	0.41638313
2. STOXX	1.085807969	0.020878674	52.00560	0.00000000
3. RAINFALLWDIF	-0.001820422	0.003984043	-0.45693	0.64772267
4. SNOWWDIF	0.003218333	0.004547034	0.70779	0.47907738
5. TEMPWDIF	0.004974830	0.019268720	0.25818	0.79626670
6. TEMPHWDIF	-0.004237516	0.014447671	-0.29330	0.76929209
7. TEMPLWDIF	-0.002147689	0.009590114	-0.22395	0.82279755
8. DAYLENGTHWDIF	-0.197506873	0.205633444	-0.96048	0.33681354
9. RADIATIONWDIF	-0.000053490	0.000023523	-2.27393	0.02297013
10. CLOUDWDIF	-0.018517670	0.011190870	-1.65471	0.09798288
11. MONDAY	0.019354779	0.032142591	0.60215	0.54707185

Prior the subprime crisis (daily data from 03/01/2000 to 17/07/2007)

Usable Observations	1966
Centered R^2	0.4963656
R-Bar^2	0.4937895
Uncentered R^2	0.4964216
Mean of Dependent Variable	-0.022490220
Std Error of Dependent Variable	2.132904070
Standard Error of Estimate	1.517528709
Sum of Squared Residuals	4502.1565657
Durbin-Watson Statistic	2.0578

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	-0.019443633	0.040343240	-0.48196	0.62983780
2. STOXX	1.307926959	0.046837054	27.92505	0.00000000
3. RAINFALLWDIF	0.004607355	0.009379580	0.49121	0.62327702
4. SNOWWDIF	0.002135591	0.009244058	0.23102	0.81729687
5. TEMPWDIF	0.039853138	0.039105833	1.01911	0.30815084
6. TEMPHWDIF	-0.016191692	0.029041322	-0.55754	0.57715869
7. TEMPLWDIF	-0.027702140	0.018904159	-1.46540	0.14281202
8. DAYLENGTHWDIF	-0.307065414	0.467128269	-0.65735	0.51095776
9. RADIATIONWDIF	-0.000117297	0.000051025	-2.29881	0.02151576
10. CLOUDWDIF	-0.032937576	0.024105283	-1.36640	0.17181192
11. MONDAY	0.026870062	0.069683914	0.38560	0.69979352

During the subprime crisis (daily data from 17/07/2007 to 09/03/2009)

Usable Observations	430
Centered R^2	0.7985482
R-Bar^2	0.7937403
Uncentered R^2	0.8015030
Mean of Dependent Variable	-0.255862675
Std Error of Dependent Variable	2.099555909
Standard Error of Estimate	0.953530648
Sum of Squared Residuals	380.96347190
Durbin-Watson Statistic	2.0523

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	-0.059490576	0.054186009	-1.09790	0.27225011
2. STOXX	0.937372695	0.031825283	29.45371	0.00000000
3. RAINFALLWDIF	-0.005501201	0.011371197	-0.48378	0.62853930
4. SNOWWDIF	0.005196500	0.011833692	0.43913	0.66056912
5. TEMPWDIF	-0.029779999	0.072905893	-0.40847	0.68292736
6. TEMPHWDIF	-0.016001007	0.045502192	-0.35165	0.72509811
7. TEMPLWDIF	0.033261881	0.043138916	0.77104	0.44068252
8. DAYLENGTHWDIF	-0.203292983	0.619094566	-0.32837	0.74263082
9. RADIATIONWDIF	-0.000074824	0.000061894	-1.20891	0.22669799
10. CLOUDWDIF	-0.041405825	0.031996333	-1.29408	0.19563767
11. MONDAY	0.056249795	0.107516374	0.52317	0.60085302

After the subprime crisis (daily data from 09/03/2009 to 31/12/2019)

Usable Observations	2822
Centered R^2	0.7162396
R-Bar^2	0.7152301
Uncentered R^2	0.7164272
Mean of Dependent Variable	0.0303406404
Std Error of Dependent Variable	1.1798477716
Standard Error of Estimate	0.6296120217
Sum of Squared Residuals	1114.3121583
Durbin-Watson Statistic	2.1747

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	-0.004747238	0.013538836	-0.35064	0.72585952
2. STOXX	0.975570536	0.022763627	42.85655	0.00000000
3. RAINFALLWDIF	-0.005465999	0.003485367	-1.56827	0.11681794
4. SNOWWDIF	0.006420042	0.003724185	1.72388	0.08472982
5. TEMPWDIF	-0.013976570	0.015105358	-0.92527	0.35482425
6. TEMPHWDIF	0.005191761	0.010748393	0.48303	0.62907674
7. TEMPLWDIF	0.012537577	0.008305489	1.50955	0.13115748
8. DAYLENGTHWDIF	-0.096864243	0.157455571	-0.61518	0.53843281
9. RADIATIONWDIF	-0.000000050	0.000015226	-0.00326	0.99739774
10. CLOUDWDIF	0.004640636	0.007981302	0.58144	0.56094499
11. MONDAY	0.012392917	0.028893681	0.42891	0.66798550

Negative interest rate period (daily data from 28/04/2015 to 31/12/2019)

Usable Observations	1221
Centered R^2	0.6927033
R-Bar^2	0.6901637
Uncentered R^2	0.6927232
Mean of Dependent Variable	0.0078213684
Std Error of Dependent Variable	0.9732742419
Standard Error of Estimate	0.5417530877
Sum of Squared Residuals	355.13065365
Durbin-Watson Statistic	2.2812

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	0.001833862	0.017745510	0.10334	0.91769130
2. STOXX	0.853208885	0.046922273	18.18345	0.00000000
3. RAINFALLWDIF	-0.010603718	0.005603406	-1.89237	0.05844167
4. SNOWWDIF	0.012013997	0.006918882	1.73641	0.08249185
5. TEMPWDIF	0.008923689	0.021270674	0.41953	0.67482874
6. TEMPHWDIF	-0.011970707	0.014562483	-0.82202	0.41106334
7. TEMPLWDIF	0.005973335	0.012397376	0.48182	0.62993202
8. DAYLENGTHWDIF	-0.018590628	0.192182361	-0.09673	0.92293739
9. RADIATIONWDIF	0.000004391	0.000019348	0.22695	0.82046325
10. CLOUDWDIF	-0.003856481	0.010788143	-0.35747	0.72073697
11. MONDAY	0.022475379	0.037494133	0.59944	0.54888136

APPENDIX 5 Linear regression of weekly values - reduced equation

Reduced equation with dependent variable OMX and statistically significant independent weather variables measured as relative weekly difference values

Full time period (daily data from 04/01/2000 to 31/12/2019)

Usable Observations	5216
Centered R^2	0.5794874
R-Bar^2	0.5792453
Uncentered R^2	0.5795131
Mean of Dependent Variable	-0.013184275
Std Error of Dependent Variable	1.683920823
Standard Error of Estimate	1.092285447
Sum of Squared Residuals	6218.3720382
Durbin-Watson Statistic	2.0750

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	-0.010525012	0.015104057	-0.69683	0.48590705
2. STOXX	1.085917468	0.020854143	52.07203	0.00000000
3. RADIATIONWDIF	-0.000055020	0.000020771	-2.64888	0.00807591
4. CLOUDWDIF	-0.019437899	0.010163465	-1.91253	0.05580867

Prior the subprime crisis (daily data from 03/01/2000 to 17/07/2007)

Usable Observations	1966
Centered R^2	0.4950209
R-Bar^2	0.4945064
Uncentered R^2	0.4950771
Mean of Dependent Variable	-0.022490220
Std Error of Dependent Variable	2.132904070
Standard Error of Estimate	1.516453651
Sum of Squared Residuals	4514.1769797
Durbin-Watson Statistic	2.0527

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	-0.015731194	0.034112782	-0.46115	0.64468922
2. STOXX	1.308465120	0.046805151	27.95558	0.00000000
3. RADIATIONWDIF	-0.000075023	0.000033819	-2.21837	0.02652937

During the subprime crisis (daily data from 17/07/2007 to 09/03/2009)

Usable Observations	430
Centered R^2	0.7973931
R-Bar^2	0.7959663
Uncentered R^2	0.8003648
Mean of Dependent Variable	-0.255862675
Std Error of Dependent Variable	2.099555909
Standard Error of Estimate	0.948371310
Sum of Squared Residuals	383.14786822
Durbin-Watson Statistic	2.0697

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	-0.042626352	0.046880344	-0.90926	0.36321368
2. STOXX	0.937652079	0.030701796	30.54063	0.00000000
3. RADIATIONWDIF	-0.000103402	0.000059437	-1.73968	0.08191581
4. CLOUDWDIF	-0.045369683	0.027041819	-1.67776	0.09339396

After the subprime crisis (daily data from 09/03/2009 to 31/12/2019)

Usable Observations	2822
Centered R^2	0.7156342
R-Bar^2	0.7153315
Uncentered R^2	0.7158222
Mean of Dependent Variable	0.0303406404
Std Error of Dependent Variable	1.1798477716
Standard Error of Estimate	0.6294999298
Sum of Squared Residuals	1116.6893155
Durbin-Watson Statistic	2.1745

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	-0.002284921	0.012010708	-0.19024	0.84912080
2. STOXX	0.975561255	0.022973135	42.46531	0.00000000
3. SNOWWDIF	0.006555555	0.003718953	1.76274	0.07794395
4. TEMPLWDIF	0.005136232	0.003050061	1.68398	0.09218615

Negative interest rate period (daily data from 28/04/2015 to 31/12/2019)

Usable Observations	1221
Centered R^2	0.6921627
R-Bar^2	0.6914039
Uncentered R^2	0.6921826
Mean of Dependent Variable	0.0078213684
Std Error of Dependent Variable	0.9732742419
Standard Error of Estimate	0.5406677543
Sum of Squared Residuals	355.75541218
Durbin-Watson Statistic	2.2831

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	0.006500549	0.015437551	0.42109	0.67369169
2. STOXX	0.854443132	0.047362309	18.04057	0.00000000
3. RAINFALLWDIF	-0.010850633	0.005507284	-1.97023	0.04881166
4. SNOWWDIF	0.011154880	0.006708641	1.66276	0.09635990