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The Seasonal Affective Disorder on Oslo Stock Exchange

Investigating snow as a potential remedy to risk aversion

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Abstract

In this thesis we investigate whether the Seasonal Affective Disorder (SAD) also known as Winter depression has an impact on the returns on Oslo Stock Exchange (OSE), and whether the effect SAD has on returns are influenced by snow cover in the time period 1990-2019. We measure the effect using the OBX total return index, the OSESX small-cap index and ten sectorial indices.

To measure the impact of the disorder we use both a method based on sunlight variation inspired by the paper *Winter Blues: A SAD Stock Market Cycle* by Kamstra, Kramer and Levi (American Economic Review, 2003), and a more modern model that is based on human behavior – the Onset/Recovery model. We find that the SAD have significantly impacted returns on some specific indices on Oslo Stock Exchange during the time period 1990-2019.

We also find that snow cover seems to significantly reduce the risk aversion associated with the SAD for three out of the twelve indices we examine, one of them being the OSESX. In addition, when controlling for the interaction between snow cover and the SAD, as many as five indices react significantly to the disorder. Though only a few indices are significant, they react in accordance to the established theory of the SAD, the SAD impacting returns negatively in the fall and positively in the winter.

The seasonal patterns are not likely to be caused by seasonal variations in turnover, but a GARCH(1,1) model suggest that time varying volatility could be a potential influence. Exploring various trading strategies inspired by the SAD, the OBX and OSESX indices suggests that returns with an excess of the market of around 2.5 percent to 5.6 could be made, depending on the index.

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1 Introduction

The topic of weather and seasons are often used as a conversational icebreaker amongst Norwegians. In later years these topics have become a hot subject of discussion amongst professors as well, even in relation to the stock market. Research suggests that the Seasonal Affective Disorder (SAD), often referred to as “the Winter Blues”, make people more averse to risk in the fall and winter period, as they are exposed to less sunlight. Financial studies on the SAD theorize that some investors may become so averse to risk that they sell their stock investments and reallocate their funds into safer alternatives at the onset of fall. As a consequence of reduced demand for risky investments, this is theorized to push stock returns down. After winter solstice however (the darkest day of the year), days slowly get more daylight and investors gradually reallocate back into risky investments, pushing returns back up.

The exploration of seasonal anomalies in equity markets have become somewhat of an established part in research on market efficiency. With regards to the SAD, many markets independent of hemispheres have proven to be significantly impacted in the past (Kamstra et al. 2003; Xu. 2015). However, few papers if any have looked at how the SAD affects the Norwegian stock market, a market that experiences great changes in the amount of daylight over the seasons. As a result, we investigate whether the SAD has a significant effect on the returns at Oslo Stock Exchange (OSE). Using Ordinary Least Squares method (OLS) we model the variation in daylight at the latitude of OSE, against returns on various indices on OSE for the time period 02.01.1990 to 30.12.2019. The indices we investigate are the OBX total return index, the OSESX small-cap index and ten sectorial indices. Our results suggest that after controlling for other known seasonal anomalies and environmental factors, only one of the sectorial indices we examine is significantly affected by the SAD. The findings that are significant however, are in line with the existing theory of SAD, suggesting that the fall period has a negative impact and the winter period a positive impact on the returns.

One of the proposed cures to the SAD is exposure to bright light. As snow reflects light quite well during a rather dark season, and occurs reliably during the period in which the SAD effect is in remission – the winter, we add to existing theory by investigating whether the presence of snow could help reduce the impact that SAD has on returns. Results suggest that there is no significant relation between snow cover and the SAD, except when using a modernized measure of the SAD in our robustness check. The modernized model supports our theory, suggesting that snow cover significantly *reduce* the negative impact SAD has on returns for three out of twelve indices. In addition, as many as five indices might be affected by the SAD after being controlled for the interaction between snow cover and the SAD.

These topics can be interesting for several reasons. If there is a consistent pattern in returns it could be possible to construct a profitable trading strategy, potentially yielding returns in excess of the market. In addition, a closer study of the SAD on Oslo Stock Exchange (OSE) could provide a better understanding of what moves the returns on the Norwegian stock market. Maybe part of fluctuations in returns that were previously thought to be caused by other factors, could in fact be explained by the SAD. This information could prove useful for private and professional investors, and academics alike.

Chapter 2, presents a more detailed explanation of what the SAD is, how it may influence financial markets and this papers hypotheses. In addition, it gives a brief overview of the most influential research on SAD, how we seek to add to this literature and a brief look at the somewhat controversial disagreement between academics on what may cause the seasonal pattern associated with the SAD. Chapter 3 presents the methods and regression models used to answer the main hypotheses. Chapter 4 presents an overview of what data has been collected, where it has been collected from, the construction of some of the more complex variables used to measure the SAD, as well as a short presentation of descriptive data. In chapter 5, we present and evaluate the results from our models with respect to the significance of the SADs impact on the OSE, and how SADs impact on returns is impacted by snow cover. The chapter also explore the robustness of our results in different ways, along with alternate explanations and the success of a trading strategy based on the SAD-effect. Chapter 6 contains the final conclusions of this paper.

2 Literary review and Hypothesis

2.1 The Seasonal Affective Disorder – A form of seasonal depression

The National Institute of Mental Health in the U.S. describe SAD as a type of depression that occurs due to a lack of exposure to sunlight. In most cases the symptoms are assumed to start around fall equinox, reach a peak at the winter equinox (the day with the least daylight in a year), before it gradually goes away when approaching spring equinox. The theory is that as days get less sunlight, the effect of SAD kicks in and gradually gets stronger until days start getting more sunlight after winter solstice. Around spring equinox, the disorder is often considered to have lost most, if not all its effect (National Institute of Mental Health 2020).

An article from Harvard Medical School titled *Shining a light on winter depression* (2019) explains that exposure to sunlight helps control the circadian rhythm – our internal clock. This rhythm is essential in helping our body to keep track of when we should wake up and be active, and when to feel tired because our body needs sleep. When the amount of daylight we are exposed to fluctuates, this rhythm can be thrown off and we are more inclined to make biased decisions (Harvard Medical School, 2019).

In relation to finance, the most widely accepted theory seems to be that the SAD make investors biased in that they become more averse to risk in the fall-winter period. This idea is backed by quite a bit of research on behavior, which suggests that there is a positive relation between anxiety or depression and risk aversion (Zuckerman, 1984; Marvel & Hartman, 1986; Carton et al., 1992). In 2003, Kamstra, Kramer and Levi published the paper *Winter Blues: A SAD Stock Market Cycle*, arguably the grandfather of papers concerning SAD within financial markets (this paper hereafter referred to as Winter Blues 2003). They found that fewer hours of daylight seemed to be associated with lower returns, which they suggest could be due to heightened risk aversion amongst investors as days get darker. Their reasoning behind why there should be lower returns as days get darker is that money is taken out of risky investments like stocks, and placed in safer assets. Thus, the demand for risky investments is lowered, which negatively impacts returns. The results were significant for a diverse set of markets from all over the world, even after having controlled for other established seasonal anomalies and factors (Kamstra et al., 2003).

2.1.1 Treatment of SAD – Snow as a potential remedy

While the main topic of this paper is to examine the presence of the SAD on the OSE, we also investigate the potential curative effect of snow. One of the most popular suggested treatments of the SAD is simply exposure to bright light. These treatments are usually performed by being exposed to a *bright light box* for a 30–45-minute period every day. Other treatments are psychotherapy also known as "Talk Therapy", medication or supplements of vitamin D (National institute of mental health, 2020).

To our knowledge the relationship between snow and the SAD or depression in general, has not been examined before. However, variables related to weather has been a part of research on the SAD in the past. Molin et al. (1996) found a significant correlation between both temperature and light exposure, and the degree of depression for patients suffering from winter depression (Molin et al., 1996). The original SAD-model of Kamstra et al. (2003) included three weather related variables cloud cover, precipitation and temperature. Their reason for including these variables is weather elements are likely to vary across seasons, and could themselves be drivers behind seasonal anomalies (Kamstra et al., 2003). In addition, Saunders (1993) found that light in form of sunlight had a significantly positive effect on stock returns using NYSE/AMEX data (Saunders, 1993).

In light of this, we propose an investigation of whether the presence of snow in form of snow cover could have a reductive effect on the risk aversion caused by SAD. We theorize that snow being white, reflects light quite well which is one of the treatments of the disorder. Snow also naturally occurs during winter, the time of year where investors according to theory on the SAD gradually become less risk averse. With snow usually starting to fall during the winter months, it could be that it is not just an increasing number of hours of daylight that "cures" the SAD, but a brightening of the environments due to snow cover.

2.1.2 How SAD may influence investors behavior and stock returns

Though presented in more detail under chapter 4, a general understanding of how the SAD is constructed can help explain how the disorder impact returns, and when the greatest changes are theorized to occur. The way SAD is measured can be thought of as a point system. As we move towards winter and days have less daylight, SAD gets stronger and has a higher score. The value of SAD on a given day is basically a function of how many hours of darkness there are in excess of 12. The score starts at zero at fall equinox, and gets higher and higher until we reach winter solstice, the day with the least amount of daylight of the year. Here the SAD-score reaches about six points, before it gradually moves back toward zero as days gradually get brighter and reach the spring equinox. Connecting this to investor behavior, each individual investor is thought to have a *tolerance-score* which describes how much SAD they can endure before they become affected and adjust their portfolio to be less risky. Figure 1 presents an example. When SAD reaches a score of 2, only person A will adjust his/her portfolio to be less risky. B and C have a higher tolerance and are not affected. When SAD reaches 4, both person A and B will adjust his/her portfolio to be less risky. Only investor C has a high enough tolerance to remain invested in stocks.

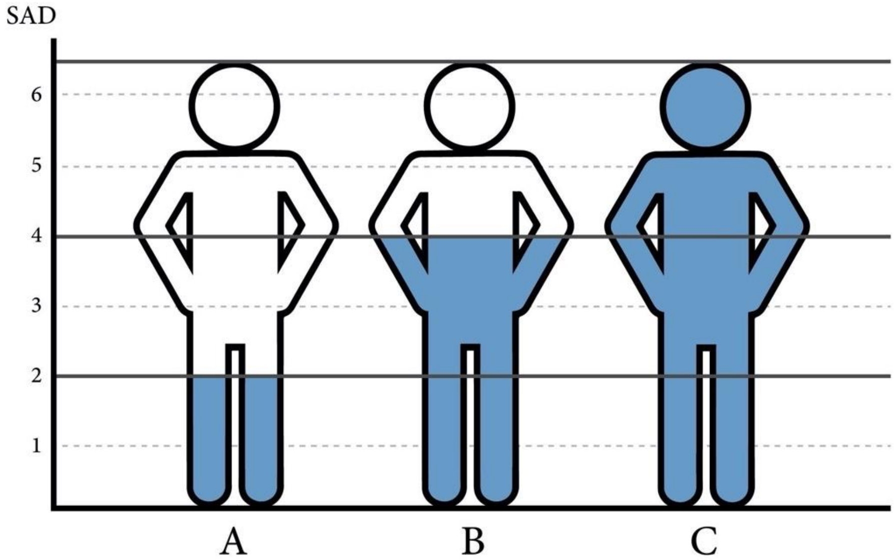

Figure 1. The level of SAD an investor can endure before adjusting his/her portfolio.

Note that it is not the *strength* of risk aversion each investor has that is central in the theory of Kamstra et al. (2003), but the number of new investors that adjust their portfolio to be less risky when a marginal change in SAD occurs. Based on their own findings, Kamstra et al. (2009) suggest that most investors that react to the SAD have a *low* tolerance score. This means that even though it is at winter solstice the greatest total number of investors are affected and have adjusted their portfolio, the greatest marginal change in portfolio composition happens around the period where the SAD-effect begins and ends. As such one would expect to find that the SAD affects returns negatively the most when it kicks in during September-October, as this is when the greatest number of investors make their move away from risky investments. Around March is when we expect the greatest marginal change in recovering SAD sufferers. As these cured investors reenter the stock market, demand for stocks increase affecting returns positively.

2.2 The history of research on SAD and seasonal patterns in financial markets

Kamstra et al. (2003) somewhat set the gold standard for research on the SAD. Their paper investigated the significance of SAD in stock markets from all over the globe and made some interesting discoveries. Especially interesting is that the more a given market deviated from the equator, the greater of an impact the SAD seemed to have (Kamstra et al., 2003). Ever since, their model has been used to investigate the presence of SAD or SAD-related patterns in different markets and for different equities.

In 2007 the trio published another paper called *Opposing Seasonalities in Treasury Versus Equity Returns* (hereafter KKL2007). The paper found evidence suggesting that the SAD may exist in the US treasury market as well. As the treasury market is generally dominated by expert traders, this implies that not even institutional or expert traders are immune to the effects of the SAD (Kamstra et al., 2007). In this paper, a new specification of the variable used to measure the SAD phenomenon was constructed, named the Onset/Recovery variable (OR). While the original variable was simply a factor of changing sunlight, and thus has the shape of a smooth sinus-curve, the OR-variable is constructed using clinical research on real people's behavior. Thus, it arguably provides a more accurate measure of the risk averse response that investors would have to the SAD (Kamstra et al., 2007).

Some have investigated whether different industries and sectors react differently to seasonal patterns. In their paper *The Halloween Effect in US Sectors,* Jacobsen and Visaltanachoti (2009) found that all sectors and industries in the US stock market showed better performance in the winter (November to April) compared to the rest of the year. However, the magnitude of the effect varied greatly between the different industries and sectors. They found that the effect was barely visible in some sectors like consumer consumption, but were quite significant in production sectors. Their reasoning for separating into several different sectors and industries, is that they were not convinced their anomaly is a market-wide phenomenon (Jacobsen & Visaltanachoti, 2009). Guo et al. (2014) also separated the market into various industries, to see if any of them were the main drivers behind any potential pattern, when analyzing the Holiday effect in the Chinese stock market. Though the anomaly did not seem to be biased towards any industry in particular, the effect did seem a little stronger for some industries rather than others (Guo et al., 2014).

Another common angle on anomalies is to see whether they are present in *small-cap* stocks as opposed to *large-cap* stocks, or the market index. Findings suggests that small sized firms tend to outperform larger firms even when riskiness is considered equal, and that small-cap firms usually are more responsive to factors that impact the market in general. This effect was popularized by Banz (1981) who found that smaller firms on the NYSE tended to have a higher return than average and larger firms, even after adjusting for risk. He further suspects that this phenomenon may have existed at least since the 1940s. A few years later Keim (1983) connected size-related anomalies to stock return seasonality. In the process, Keim found evidence suggesting that the month of January had abnormal returns that were on average substantially larger compared to the other months of the year. The relation between size and abnormal returns were also *negative*, implying that the smaller the size the greater the abnormal return. On top of this, he finds that almost 50% of the small-firm effect may be explained by excess returns in the month of January (Keim, 1983).

2.3 SAD versus the Sell-in-May anomaly – The same seasonal pattern?

A year before Kamstra et al. (2003) produced their paper on the SAD, Bouman & Jacobsen (2002) published a paper on an anomaly that is very similar to the SAD. The paper is called *The Halloween Indicator - Sell in May and Go Away: Another Puzzle*. Much like Kamstra et al. (2003), their theory is based on dividing the calendar year into two separate periods to examine whether there is a difference in returns. Their research suggests that returns in the period November-April is significantly higher than the rest of the year. As a conclusion, Bouman & Jacobsen suggest that investors would be better of liquidating their stock portfolio and invest in risk-free assets from May to November (Bouman & Jacobsen, 2002). This strategy is very similar to the one that *Winter Blues* (2003) suggests. *Winter Blues* (2003) find evidence of quite significant excess returns if following a *pro-SAD* strategy (having a long position in the market for the entire period when SAD is in effect). Initially, it might seem a little odd to stay invested during the entire SAD-period if the fall period has a significant negative impact on returns. *Winter Blues* (2003) do however find that a pro-SAD strategy provides greater profits than betting against it. (Kamstra et al., 2003). The two strategies and the overlap between them can be seen in figure 2. The slice in the figure highlights the period from 21st of September to 31st of October. This period represents a particularly interesting deviation between the two strategies that is addressed in greater detail under chapter 2.3.1.

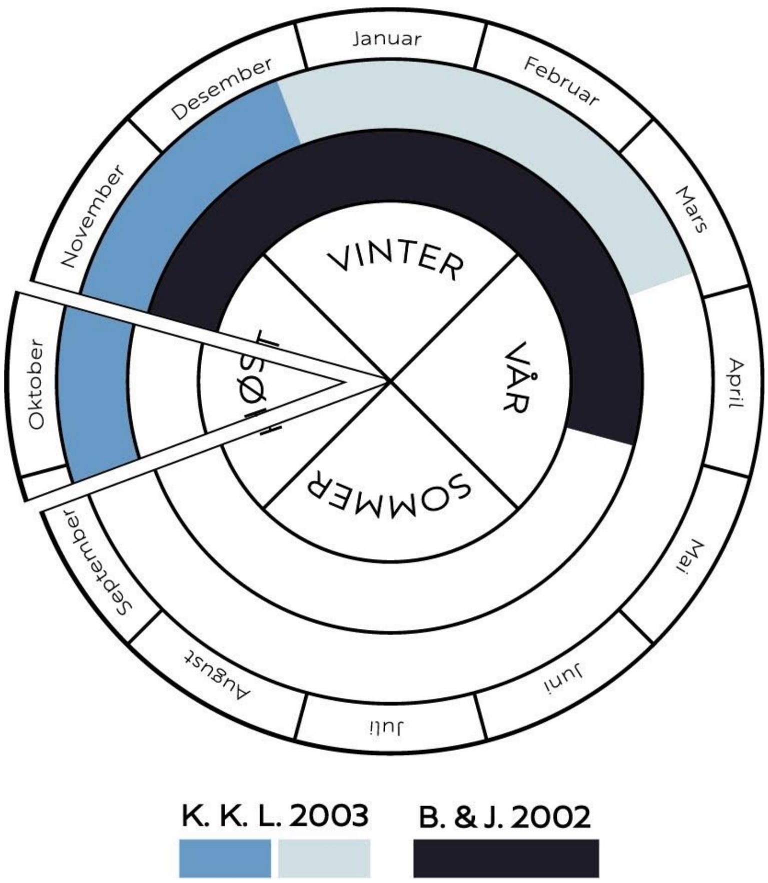

Figure 2. The trading strategies of Winter Blues (K.K.L.2003) and Sell-in-May (B.&J.2002) The marked periods are where the two papers suggest investors should be long in the stock market. In the left-part of the K.K.L.2003 strategy SAD is expected to have a negative impact on returns. In the right-part of the K.K.L.2003 strategy SAD is expected to have a positive impact on returns.

There has been somewhat of a discussion between Kamstra & Co and Bouman & Jacobsen. They both seem to talk about the same seasonal pattern, and suggest roughly the same investment strategy, but their explanations as to what caused the pattern are quite different. *Winter Blues* (2003) recommend staying invested because of a strategy that provides *excess returns* during the fall-winter, Bouman & Jacobsen suggest staying invested due to *less-than-average* returns during the summer-fall. Bouman & Jacobsen are not the only ones who have been critical to the theory of the SAD effect. Kelley & Meschke (2010) re-examined the SAD anomaly and argue that the anomaly could be explained by a simple dummy (Kelly & Meschke, 2010). Jacobsen from the Sell-in-May paper also wrote another paper with Marquering (2008) where they critique two seasonal studies, *Winter Blues* being one of them (Jacobsen &

Marquering, 2008). Kamstra & Co have time and time again been able to defend their claims however, and their theory seems to still stand strong in academic circles, being widely used even in recent academic articles (Kamstra et al., 2009; Kamstra et al., 2012; Xu. 2015).

2.3.1 Why the debate concerning SAD and the Sell-in-May effect matters

The hypothesis of SAD affecting the stock market has not been without its controversies. As seen from figure 2, it could very much be the case that Bouman & Jacobsen and Kamstra et al. (2003) are talking about the same pattern, and it is not obvious that it is the SAD that best explains said pattern. Why then should we choose the SAD approach for this paper? Though the theory presented in *Winter Blues* (2003) is not without its flaws, we argue its authors make some strong arguments for their angle at this seasonal pattern.

First of all, the hypothesis presented in Winter Blues (2003) is supported and even inspired by the medically recognized condition of SAD. Meaning that the concept of SAD existed long before Kamstra & Co even started writing their paper. They are merely looking at how a widely recognized disorder may affect the stock market (Kamstra et al., 2003). Bouman & Jacobsen on the other hand could be criticized for not presenting a clear explanation or theory as to why their suggested pattern should hold, other than it being based on an old saying. Only after having presented their results in the Sell-in-May paper, do they come up with theories as to what may have caused the effect. Even then, Bouman & Jacobsen themselves point out that none of their explanations provide a solid explanation for the seasonal puzzle (Bouman & Jacobsen, 2002).

Another argument is that while the Sell-in-May effect seemingly has a longer tradition as an anomaly in stock trading, the paper of Kamstra et al. (2003) have been cited in more than double the number of academic papers. While this alone hardly proves that their paper is more accurate than Bouman & Jacobsen´s, one could make the argument that their theory has received a wider acceptance than the Sell-in-May effect within academic circles in more recent years. A search on Google Scholar reveal that *Sell-in-May* has been referenced to in 556 academic papers and articles as opposed to *Winter Blues'* 1154 references at the time of writing (Google Scholar, 2021a; 2021b).

Finally, one can argue *Winter Blues* (2003) present evidence that could explain why Bouman & Jacobsen (2002) would find negative returns in the summer-fall period in the first place. Kamstra et al. (2003) finds a drop in returns during the fall portion of the SAD period, as their fall-dummy shows significantly negative returns for almost all their tested markets. September and October are the months with the lowest returns and where the negative SAD effects are assumed to be the strongest, as represented by the first K.K.L. 2003 portion in figure 2. Around December 21st the SAD-effect turns. People are still affected by the disorder, but people gradually recover, and the SAD-effect is theorized to have a net positive impact on stock returns, as represented by the second K.K.L.2003 portion in figure 2. Bouman & Jacobsen's strategy is virtually the same. They suggest exiting the market in May to re-enter in November due to lower-than-average returns during the months May through October. In November however, *Winter Blues* (2003) theorizes that most of the investors that will change their investments due to SAD has already done so, and there is mostly just upside related to people being cured of their SAD as soon as we pass the winter equinox. It is quite possible that the lower-than-average return Bouman & Jacobsen found during the May-November period could be explained by the early parts of the SAD-effect. It is difficult to make the counter argument as Bouman & Jacobsen does not provide a clear explanation to why there should be fluctuations in returns during the seasonal pattern. The overlap between the periods is shown as the "slice" in figure 2.

In the end, we argue that the SAD provides the most reasonable explanation. It is also broadly accepted as a possible explanation to the seasonal pattern, and it could potentially explain at least some of the less-than-average returns that Bouman & Jacobsen find during the summer-fall period. It seems harder to make the counter argument. As a result, we feel that investigating this seasonal pattern using the methods and theories attached to the SAD-effect is the most appropriate for this paper.

2.4 What we use from the literary review

The SAD has been tested and found to have a significant impact on financial assets in many different countries, likely impacting both private and institutional investors. Though the Swedish stock market was tested by Kamstra et al. (2003), we have not succeeded in finding any papers on how SAD affects the Norwegian stock market. Norway as a country lies quite far away from the equator and as such experiences quite significant changes in hours of daylight across the seasons. This makes it a particularly interesting market to study in relation to SAD. If it is indeed possible to find signs of the SAD affecting stock returns, or even build a profitable trading strategy around the SAD, the Norwegian stock market seems like an ideal candidate.

As such this paper could hopefully provide a slight progression in mapping the effects of the SAD around the globe.
In addition to this, while several weather phenomena have been controlled for in the past, no papers have examined whether the SADs effect on return is affected by snow. This seems especially interesting as the dates of when snow occur and SAD suffers are cured are a close match.

2.5 Research question

Motivated by previous research, this paper seeks to answer two hypotheses. First, we test whether the SAD is likely to be a significant predictor of returns on the OSE, hereby referred to as *hypothesis one*. The Norwegian market has to our knowledge not been tested for SAD specifically before, and the existence of SAD is somewhat of a prerequisite for the second hypothesis we propose. The idea is to test the following hypothesis for various indices on the OSE:

H_0: The Seasonal affective disorder does not affect returns of index X
H_a: The Seasonal affective disorder does affect returns of index X

With our second hypothesis we wish to test if the SAD is affected in any way by snow cover, hereby referred to as *hypothesis two*. To our knowledge, this is a unique angle to the SAD anomaly, a way in which we contribute to the work of seasonal anomalies in the stock market. The theory is that the presence of snow will alter the impact SAD has on returns:

H_0: The Seasonal affective disorders effect on returns is not affected by snow cover
H_a: The Seasonal affective disorders effect on returns is affected by snow cover

As research suggest that SAD might manifest itself differently across different industries and indices, these two hypotheses are tested on the OBX total returns index, the OSESX small-cap index and various sectorial indices on the OSE.

2.6 Our contribution

The usual approach when analyzing the SAD is to test the effect using the returns of the broad market index for that given market (Kamstra et al., 2003; Bouman & Jacobsen, 2002). Previous research does however suggest that certain industries could be the main drivers behind the seasonal pattern, and small-cap stocks are seemingly being more responsive to seasonal patterns and anomalies in general. Based on this, we examine the impact that SAD has had on the OSE in three different ways: First we use the OBX total return index as measure of the overall effect SAD has had on the OSE during the period we examine, following the approach used in Winter Blues (2003) as closely as possible. Secondly, we examine the effect the SAD has had on the OSESX small cap index, motivated by the many anomalies that has been found to be present in small cap indexes in the past. Finally, we investigate the SAD-effect in sectorial indices. Dividing the stock market into different sectors could hopefully give more detail as to how the anomaly manifests itself on the OSE. This knowledge could be relevant for example when composing trading strategies, or for academics mapping what factors impact the market.

To explore whether other factors could explain any patterns we may find, we also run our data set through some additional robustness checks. We explore whether seasonal variations in returns could be caused by time varying volatility using a GARCH(1,1) model, and we investigate whether any pattern in returns could be explained by variations in liquidity. As different ways of measuring the SAD-effect have been proposed in academic literature, we investigate whether different specifications of the anomaly yield different results, using the original SAD-measure from *Winter Blues* (2003), and the more behavioral based Onset/Recovery measure. And finally, it's been almost two decades since the paper by Kamstra et al. (2003) was published. It could be interesting to see if the findings that were obtained in 2003 still holds true in more recent times. The trading landscape in 2003 compared to today is hardly comparable, especially after the internet has become so much more common for private use and recreation, and some banks today even providing commission-free online trading. This could have changed the impact that SAD has today compared to what it did in 2003. To check whether our suspicions hold true, we investigate whether the periods before- and after *Winter Blues* (2003) yield different significance on the SAD effect.

3 Methodology

To test our two hypotheses, we use OLS regressions along with MacKinnon and White (1985) heteroskedasticity robust standard errors. We will be testing these hypotheses for 12 different indices, covering the OBX total return index, the OSESX small-cap index and ten sectorial indices. The following present the different specifications of regressions that we will run for each hypothesis and our robustness checks. Note that we separate between *models* and *equations*. With models we refer to regression models that are being used to test our hypotheses. Equations are used to describe non-regression computations. We make this distinction as there are a few different regressions to keep track off. Hopefully this will make it a little easier to keep track of them when compared to each other.

3.1 Models for hypothesis 1 – Different specifications of the SAD regression equation

The study of how the SAD might affect the stock market has developed over the years, which has spurred different theories and approaches on how to correctly measure the disorder. Most papers opt to use several models with the SAD specified in different ways (Kamstra et al., 2009; Kelley & Meschke 2010; Xu. 2015). In this paper we use two different models to measure the SAD, with the only difference between the two being how they measure the SAD-phenomenon. The first model is the original model presented in *Winter Blues* (2003), which uses the standard SAD-variable to measure the effect the depression has on stock returns. The second model use the Onset/Recovery variable to measure the disorder. The OR specification of the SAD is based on human behavior in relation to changing sunlight, whereas the SAD is simply based on sunlight patterns alone. As such, any differences in results between the two models will likely be attributed to human behavior. The original SAD model is used as a baseline model, and the OR model as a robustness check to see if there are any differences across the two models.

3.1.1 The Winter Blues (2003) SAD regression

Most papers about SAD in the stock market use a method that was established by Kamstra et al. (2003). The regression they use is shown in model 1. We run this regression for each relevant index, which allows us to see how a given index has been affected by the SAD after the other variables in the regression is controlled for. This model is an *auto-regressive model*, which is usually a standard when analyzing stock returns (Akgiray, V., 1989; Pagan, A. & Schwert, W., 1990; Susmel, R. & Engle, R. F., 1994; Donaldson, G. R. & Kamstra, M., 1997, as cited in Kamstra et al., 2003). Such a model allows us to control for autocorrelation by including observations from past periods on the dependent variable. The original *Winter Blues* (2003) SAD-model proposes the use of *two* lags on the dependent variable, which has become the standard practice in most SAD related papers (Xu, 2015, p. 39; Kamstra et al., 2003; 2012; Kelly & Meschke, 2010). The model used in this paper follows this tradition. Amongst other things, this makes comparisons with other papers more appropriate.

(Mod. 1)
$$\begin{aligned} r_t = \; & \beta_0 + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{SAD} SAD_t + \beta_{Fall} D_t^{Fall} \\ & + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{Temp} Temp_t \\ & + \beta_{CloCov} CloCov_t + \beta_{Precip} Precip_t + \varepsilon_t \end{aligned}$$

Table 3.1 Description of the Winter Blues (2003) variables

Name of variable	Description
r_t	Logarithmic returns for time period t
$\rho_1 r_{t-1}, \rho_2 r_{t-2}$	Lagged dependent variables. Controls for residual autocorrelation
SAD_t	If the date is between September 21st and March 20th the variable ranges from 0 to 6.43, otherwise equals to 0
D_t^{Fall}	Dummy separating the period of fall and winter, where the period from September 21st to December 20th equals to 1, otherwise 0
D_t^{Monday}	Dummy = 1 if Monday, otherwise 0
D_t^{Tax}	Dummy = 1 for the five first and the last trading day of year, otherwise 0
ϵ_t	Error term

3.1.2 The Onset/Recovery variable

In 2007 Kamstra et al. introduced the Onset/Recovery (OR) variable. Their claim is that the OR variable more accurately display how the SAD impacts the stock market, as it has a value for every day of the year as opposed to the SAD variable that only has non-zero values between fall- and spring-equinox. Thus, there is no need to include the fall-dummy, which reduces the number of parameters in the equation. All in all, KKL2007 claim that the results from the two models should be very similar (Kamstra et al., 2007). More recent papers have taken to use both the SAD and the OR specification in order to test the robustness of either regression (Kelly & Meschke, 2010; Xu, 2015).

(Mod. 2)
$$\begin{aligned} r_t = \; & \beta_0 + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{OR} OR_t + \beta_{Monday} D_t^{Monday} \\ & + \beta_{Tax} D_t^{Tax} + \beta_{Temp} Temp_t + \beta_{CloCov} CloCov_t \\ & + \beta_{Precip} Precip_t + \varepsilon_t \end{aligned}$$

3.2 Models for hypothesis 2 – Snow covers impact on SAD-related returns

To test our second hypothesis, we use four different base models. The two first models (model 3 and 4) simply allow us to see what impact snow cover has on the overall returns of a given portfolio, while the remaining two allows us to investigate whether snow cover has an impact on SAD-related returns. Note that the two last models are split into two separate specifications, leaving us with a total of six models. Models 5 and 7, and 6 and 8 respectively, are virtually identical. The only exception is that SAD and Fall are being replaced by OR in model 6 and 8 respectively.

Model 3 regress the variable for snow cover (SnoCov) on returns which allows us to see if snow cover has any impact at all on the returns of a given portfolio:

(Mod. 3)
$$r_t = \beta_0 + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{SnoCov} SnoCov_t + \varepsilon_t$$

In the second step we include the rest of the independent control variables that were used in regression model 1 and 2. The SAD, Fall and OR variables are excluded for now. This allows us to see if SnoCov has any explanatory power on returns after being controlled for other relevant variables:

(Mod. 4)
$$\begin{aligned} r_t = \; & \beta_0 + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{Monday} D_t^{Monday} \\ & + \beta_{Tax} D_t^{Tax} + \beta_{Temp} Temp_t + \beta_{CloCov} CloCov_t \\ & + \beta_{Precip} Precip_t + \beta_{SnoCov} SnoCov_t + \varepsilon_t \end{aligned}$$

Models 5 and 6 are essentially the same as model 1 and 2, used to test the first hypothesis. They include all the initial independent variables, but add the new SnoCov variable as well.

This should allow us to see if the inclusion of SnoCov changes the significance or size of the SAD variable:

(Mod. 5)
$$
\begin{aligned}
r_t = \quad & \beta_0 + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{SAD} SAD_t + \beta_{Fall} D_t^{Fall} \\
& + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{Temp} Temp_t \\
& + \beta_{CloCov} CloCov_t + \beta_{Precip} Precip_t + SnoCov_t + \varepsilon_t
\end{aligned}
$$

(Mod. 6)
$$
\begin{aligned}
r_t = \quad & \beta_0 + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{OR} OR_t + \beta_{Monday} D_t^{Monday} \\
& + \beta_{Tax} D_t^{Tax} + \beta_{Temp} Temp_t + \beta_{CloCov} CloCov_t \\
& + \beta_{Precip} Precip_t + \beta_{SnoCov} SnoCov_t + \varepsilon_t
\end{aligned}
$$

The last two models are exactly like model 5 and 6, except that we introduce an interaction variable between SAD and OR respectively, and SnoCov. This variable should allow us to see how much the SAD-related returns change, with a marginal change in snow cover:

(Mod. 7)
$$
\begin{aligned}
r_t = \quad & \beta_0 + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{SAD} SAD_t + \beta_{Fall} D_t^{Fall} \\
& + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{Temp} Temp_t \\
& + \beta_{CloCov} CloCov_t + \beta_{Precip} Precip_t + \beta_{SnoCov} SnoCov_t \\
& + \beta_{SAD\_SnoCov} SAD_{t}\_SnoCov_t + \varepsilon_t
\end{aligned}
$$

(Mod. 8)
$$
\begin{aligned}
r_t = \quad & \beta_0 + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{OR} OR_t + \beta_{Monday} D_t^{Monday} \\
& + \beta_{Tax} D_t^{Tax} + \beta_{Temp} Temp_t + \beta_{CloCov} CloCov_t \beta_{Precip} Precip_t \\
& + \beta_{SnoCov} SnoCov_t + \beta_{OR\_SnoCov} OR_{t}\_SnoCov_t + \varepsilon_t
\end{aligned}
$$

3.3 Fama & French three - factor model

To explore whether there is a seasonal pattern in the returns at all, we use the Fama and French three factor model (1992). This model is an extension of the CAPM with the addition of two anomalies - the *book-to-market equity ratio* and *market capitalization*. By regressing the three factors on each portfolios excess returns, we can analyze the alpha (constant) we get from this model. The alpha should show us any extraordinary returns that the given period would have, when controlled for the Fama French factors (FF3):

(Eq. 1)
$$
r_t - r_f = \alpha + \beta_{1i}(r_m - r_t) + \beta_{2i}(SMB) + \beta_{3i}(HML) + \varepsilon_t
$$

To investigate if any season relevant to our thesis show risk-adjusted returns in excess of the market, we divide the year into three separate periods – fall, winter and spring-summer. Doing this allows us to investigate two things; First, it allows us to compare the three periods to see if they follow the expectations set by the SAD theory, of fall and winter having higher returns than the spring-summer period, with winter having the highest overall returns. Second, the alpha will be risk adjusted and if we do not find any significantly positive alphas, it could be that the seasonal returns could be caused by one of the factors rather than changes in risk aversion.

3.4 GARCH(1,1)

It is possible that extraordinary returns in a specific period is a compensation for higher volatility rather than a change in investor behavior as the SAD effect suggests. When OLS is used, there is an underlying assumption that the volatility of the returns error term is constant over time (assumed homoscedasticity). When analyzing financial timeseries however, it is common to assume that the error term is *not* constant over time (Brooks, 2018, p. 423). If a Lagrange Multiplier-test (LM-test) yield significant results, the OLS does not provide the best linear unbiased estimates, and a GARCH(1,1) model would be more appropriate as it accounts for time varying volatiltiy.We run the GARCH(1,1) on the Model 1 specification, and control for the other variables that vary over time; temperature, cloud cover and precipitation. If the ARCH and GARCH coefficients of a GARCH(1,1) model are significant we have evidence suggesting the volatility of returns vary over time. Ergo, if the coefficients are significant lags of the error term help predict future volatility and the volatility is not truly random, suggesting that patterns of returns could be a reflection of patterns in volatility, not just changes in daylight. The GARCH(1,1) models look as follows:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \theta_{SAD} SAD_t + + \theta_{Fall} D_t^{Fall} + \theta_{Temp} Temp_t + \theta_{CloCov} CloCov_t + \theta_{Precip} Precip_t + \varepsilon_t \quad \text{(Eq. 2)}$$

In this equation, σ_t^2 is the conditional variance, the constant ω (long term mean of the variance), ε_{t-1}^2 is the ARCH term (the most recent daily percentage change), σ_{t-1}^2 is the GARCH term (variance of the prior period), and θ are the control variables for the model.

3.5 Turnover

There is a possibility that any seasonal fluctuation in returns could exist due to a changing pattern in liquidity on the OSE over the different seasons. To explore whether any seasonal fluctuation in returns could be caused by seasonal changes in liquidity on the OSE, we explore how the results in model 1 changes when adding liquidity measures. We use turnover to measure liquidity of stocks, and explore its impact using two different models. Our first regression (Eq. 3) simply adds the turnover variable (TO) and an interaction variable between turnover and SAD (SAD_TO) to the original SAD-model. If the impact SAD has on returns is indeed affected by turnover, this should show itself through the interaction variable between SAD and turnover being significant. In the second regression (Eq.4) we add the snow cover variable. Comparing the results we get on SnoCov in this model to the ones in model 7, we can see if snow cover seems in any way to be affected by liquidity. If the coefficients do not change much in significance, size or sign, it is likely that the impact snow cover has on returns or the SAD-effect is not affected by liquidity.

(Eq. 3)

$$\begin{aligned} r_t = \quad & \beta_0 + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{SAD} SAD_t + \beta_{Fall} D_t^{Fall} \\ & + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{Temp} Temp_t \\ & + \beta_{CloCov} CloCov_t + \beta_{Precip} Precip_t + \beta_{TO} TO_t \\ & + \beta_{SAD\_TO} SAD\_TO_t + \varepsilon_t \end{aligned}$$

(Eq. 4)

$$\begin{aligned} r_t = \quad & \beta_0 + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{SAD} SAD_t + \beta_{Fall} D_t^{Fall} \\ & + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{Temp} Temp_t \\ & + \beta_{CloCov} CloCov_t + \beta_{Precip} Precip_t + \beta_{TO} TO_t \\ & + \beta_{SAD\_TO} SAD\_TO_t + \beta_{SnoCov} SnoCov_t + \varepsilon_t \end{aligned}$$

3.6 Investigating the resilience of SAD - Before and after Winter Blues (2003)

It could be the case that the significance of the anomaly has changed over the years. The market could become more efficient over time, and investors are likely to be more aware of the different anomalies as people write about them. To check if the SAD is likely to have changed over time, the data set is split into two different periods – one from 02.01.1990-02.01.2003 covering the period before *Winter Blues* (2003) raised awareness around the SAD-effect, and another period from 02.01.1990-30.12.2019 covering the period after *Winter Blues* (2003) and up till recent times. Since we have already done a more in-depth analysis on the coefficients under section 5.1 and 5.2, we will mainly focus on the changes in significance between the two periods. If the significance of the disorder has changed over time, we should be able to identify this by looking for changes in significance on the coefficients for SAD between the two periods.

We test this break for three models. First, we test if there are differences over time using the original SAD-model, model 1. We do the same to model 5 including the Snow cover- variable, and finally we investigate potential differences in model 7 with both snow cover and the interaction between snow cover and SAD. As anomalies are assumed to disappear over time, as suggested by the efficient market theory, we expect the 1990-2002 period to show more significant coefficients than the period from 2003-2019.

4 Data

4.1 Measuring SAD and OR

In this paper, there are mainly three variables that are relevant when analyzing the effect of SAD, two of them being directly tied to how we measure the disorder. Those are the variables *SAD* and D_t^{Fall}in model 1, and the OR variable in model 2.

4.1.1 The SAD variable

As a data-point, the SAD variable is a way of measuring the excess number of hours of no sunlight at a specific latitude. The SAD variable assumes that risk averse behavior related to the depression, kicks in at fall equinox and falls of completely at spring equinox. The exact day of when an equinox occurs could vary by a day or two depending on the year. A common approach is to simply use the dates September 21st and March 21st as thresholds (Kamstra et al., 2003; Xu, 2015). As a result, the value of SAD for a specific day is found by using the following rule:

(Eq. 5) $$SAD_t = \begin{cases} H_t - 12 & for\ trading\ days\ in\ the\ fall\ and\ winter \\ 0 & otherwise \end{cases}$$

The variable (H_t) describes the number of hours when there is no sunlight for any given day, ergo the time from sunset to sunrise. The SAD variable is thus constructed such that if the day has more than 12 hours of darkness, the SAD kicks in and gets a positive value. The reason 12 hours is being used as a benchmark is that, is that it is roughly the average number of hours of night over the entire year at any location (Kamstra et al., 2003). Note also that when the date falls outside of the seasons where SAD is assumed to have an effect, the value of SAD equals to zero. To find the value of SAD we must find the value of H_t for each relevant day. Kamstra et al. (2003) suggests a two-step-process where we *first* find the suns declination angle (λ) and then use that to compute the number of hours of darkness (H_t).

The formula for finding the declination angle (λ) at a specific date for a specific latitude (σ) is as follows:

(Eq. 6)
$$\lambda_t = 0{,}4102\ x\ sin\left[\left(\frac{2\pi}{365}\right)(julian_t - 80{,}25)\right]$$

Using the latitude of the market (σ) and date of the Julian calendar ($julian_t$), one can find the suns declination angle (λ)

Once the declination angle of the sun at the specific latitude is computed, the number of hours at night (H_t) can finally be found using a similar formula. This process is repeated for every day of the year, so that every day has its unique SAD value appropriate for that latitude. A short summary of all the variables required for computing the value of SAD on a given date is shown in table 4.1:

(Eq. 7)
$$H_t = 24 - 7{,}72\ x\ arccosine\ \left[-\tan\left(\frac{2\pi\delta}{360}\right)\tan\left(\lambda_t\right)\right]$$

Final step – Formula for finding number of hours of night (H_t) when the suns declination angle (λ) is known

Kamstra et al. (2003) theorizes that risk aversion increases from autumn equinox and decrease from winter solstice to spring equinox from where the SAD is supposed to more or less disappear entirely. Figure 3 displays how the value of SAD varies across the fall and winter seasons. The graph begins at fall-equinox (September 21st) and each column is thus showing the value of SAD at the 21st each month. It reaches its highest value of 6,426 at December 21st:

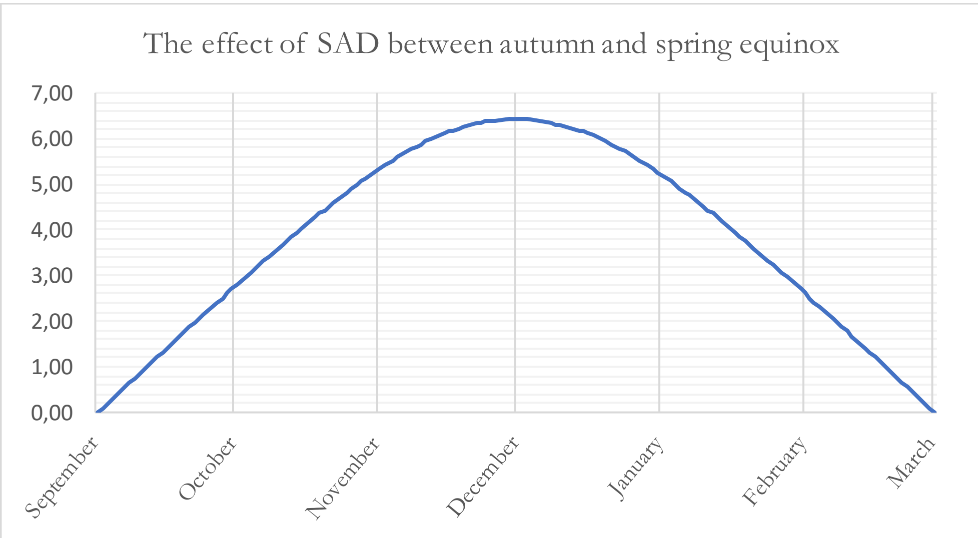

Figure 3. The value of SAD between autumn and spring equinox.

Table 4.1 Variables required for calculating SAD at given date (t)

Variables to calculate the SAD measure	Description
SAD	Variable showing the number of excess hours of darkness beyond 12 hours on a given day.
σ	The latitude of the given market/ stock exchange
λ	Declination angle of a specific market
H_t	Time from sunset to sunrise in a specific location
Julian	The day of the year measured by the Julian calendar (1. January = 1, 2. January = 2, etc.)
Arccos	The Arccosine function

4.1.2 The fall variable

Kamstra et. al (2003) theorizes that the SAD-effect differs over the year with returns in the fall being negatively impacted, and returns in the winter being positively impacted by the disorder. To capture the difference between fall and winter, a dummy variable for fall is introduced (D_{Fall}). In short, this dummy allows for investigation of whether there is a difference in the impact of SAD in the fall as opposed to the one in the winter. Fall season is defined as the period between autumn equinox and winter solstice, which is September 21st to December 20th (Kamstra et al., 2003).

(Eq. 8)
$$D_t^{Fall}\begin{cases} 1 & for\ trading\ days\ in\ the\ fall \\ 0 & Otherwise \end{cases}$$

If the fall-dummy is significant it implies that SAD does indeed affected returns differently between fall and winter, which allows for a more detailed description of how SAD affects returns. If the fall-dummy is insignificant it implies that the impact of SAD is symmetric across the winter and fall periods, and there is no significant difference in SAD-related returns amongst the two periods (Kamstra et al., 2003).

4.1.3 The Onset Recovery (OR) variable

The OR-variable is basically another way to measure the SAD-effect. There is a possibility that the fall dummy and the SAD variable (which simply measures length-of-night) could pick up something that affects returns other than the SAD itself. By using the OR variable, KKL2007 attempts to remedy this issue. The OR variable has numerical values for the entire year, as opposed to the SAD which only has non-zero values from fall-equinox to spring-equinox. The OR-variable expresses the proportion of people who suffer from SAD. Its values are constructed so that it has its highest values in the fall, when the marginal increase in number of SAD-related risk averse investors is the greatest. Its lowest values are in the spring, when the greatest marginal increase in investors cured from SAD occurs. The data for the OR variable is available to the public on the home page of Mark Kamstra (Kamstra. 2021). Figure 4 show a visual representation of this variable. The most notable difference between OR and the SAD variable is that the pattern of the OR variable is less smooth, reflecting the behavioral pattern of investors rather than purely changes in daylight.

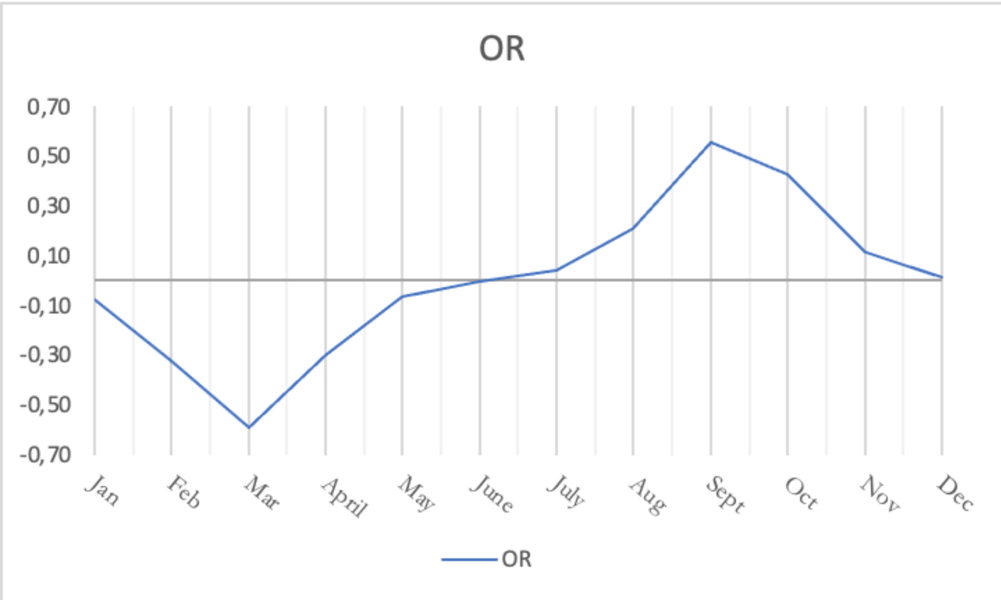

Figure 4. The value of the OR variable from January to December.

The OR variable constructed by Kamstra et al. (2007) is based on the latitude of the NYSE. It has been suggested that OR can be adjusted to fit the latitude of choice by simply computing the relation of any given latitude and the latitude of NYSE (Xu, 2015).

As we are interested in the Norwegian stock market specifically, we use this conversion formula for the latitude of Oslo, as that is the city in which the OSE is located:

(Eq. 9) $$\Upsilon_i = \frac{Latitude_{City_i}}{Latitude_{NewYork}}$$

Relation between any given latitude and the latitude of NYSE

(Eq. 10) $$OR_{City_i} = \Upsilon_i \ x \ OR_{NewYork}$$

OR adjusted to fit any given city

4.1.4 Descriptive statistics of SAD and OR

Table 4.2 Descriptive Statistics for the SAD and OR variable

Variables	Obs	Mean	Std. Dev.	Min	Max	Skew.	Kurt.
SAD	7526	1.895	2.378	0	6.426	.788	1.987
OR	7526	.006	.314	-.633	.633	-.024	2.795

4.2 Snow cover and weather variables

The weather data collected are daily observations from the period 02.01.1990 to 30.12.2019 and is provided by *The Norwegian Meteorological Institute* (2021), through their webservice seklima.met.no. Since we're studying SAD on Oslo Stock Exchange the weather station at Blindern in Oslo is chosen to document the weather that investors and traders in close proximity to the OSE will be exposed to. To study the different effects of weather we use observations on four different elements: temperature, cloud cover, precipitation and snow cover. Our proposed new variable snow can be measured in several different ways including snow fall, snow cover and snow depth. In this paper we choose snow cover as the measure of snow. The reason for our choice is that it seems to best fit our hypothesis. We hypothesize the reflection of sunlight on snow, or just the white color of snow in general leads to increased exposure to bright light. We argue that snow reflects light the best when it is on the ground as opposed to snow fall, and snow cover also mean that the environments are brighter altogether.

Table 4.3 Specification of weather variables

Panel A: Description

Weather element	Variable	Description
Temperature	Temp	Daily arithmetic mean temperature of 24 hourly values in Celsius
Precipitation	Precip	The total amount of precipitation measured as a daily sum in millimeters
Cloud cover	CloCov	Arithmetic mean of three daily observations at 0600, 1200 and 1800. The measurement unit is in octas, where 0 equals clear sky and 8 total cloud cover
Snow cover	SnoCov	Daily observation that ranges from 0 to 4, where 0 equals no snow and 4 equals completely covered ground observed in 1 km circumference from the weather station.

Panel B: Descriptive statistics

Variables	Obs	Mean	Std. Dev.	Min	Max	Skew.	Kurt.
SnoCov	7526	1.025	1.675	0	4	1.115	2.324
Temp	7526	7.055	8.032	-18.1	25.9	-.128	2.248
Precip	7526	2.256	4.907	0	72.8	3.697	23.573
CloCov	7526	5.538	2.163	0	8	-.619	2.283

4.3 The January effect and the Weekend effect

As presented in chapter 3, control variables for the January- and the Weekend-effect are included in the models to make sure we do not mistake any returns that may be caused by these anomalies, with the returns associated with the SAD. These anomalies are included as simple dummy variables that isolate specific dates associated with the relevant anomaly. In what follows, there will be a short description of the anomalies that are usually considered relevant when testing the SAD and are used as control variables in our models.

4.3.1 The January effect (The tax effect)

The January effect is one of the more famous seasonal anomalies in finance and focuses on market returns in the first month of the year which seems to be generally larger than the returns in the rest of the year. The effect was first introduced by Wachtel in 1942, and seems to have persisted over the years, and quite a few popular papers have been written since it first got discovered (Wachtel, 1942; Thaler, 1987; Moller & Zilca, 2008; Gultekin & Gultekin, 1983). In this paper we will often refer to the January effect as the *tax-effect*, as the anomaly is suspected to be related to investors selling off stocks to realize tax-loss benefits on stocks at the end of the year. As the January effect has gradually become known as the tax effect, modern studies have chosen to only include the last date of the past year, and the first days of the new year. We measure the tax-effect in the same manner with a dummy that equals one if the date is the last trading day of a year or in the five first trading days of a year, and equals zero if otherwise (Kamstra et al., 2003).

4.3.2 The Weekend effect

The weekend effect is another anomaly that is well documented and have remained relevant over the years. One of the most popular papers on the topic was published by French (1980). He found that returns on the S&P 500 index were in average negative on Mondays, while the highest returns were earned on Wednesdays and Fridays. Several other prominent papers have found the same results, even in more modern times (Gibbons & Hess, 1981; Birru, 2016). In this paper we measure the effect by using a dummy that is equals one if the day is a Monday, and zero if otherwise.

4.4 Stock market data

To study the effect of SAD in the Norwegian stock market, we examine the Oslo Børs Total return index (OBX), Oslo Børs Small cap index (OSESX*)* and ten sectorial indices representing different industries on Oslo stock exchange (OSE). We have collected three main types of stock market data for this thesis, those three being stock returns for all the indices, data for daily turnover on the entirety of OSE and factors for the Fama French three factor model.

4.4.1 Stock market returns and Fama French factors

The data on returns for the OBX and the sectorial indices, as well as turnover and Fama French factors, are provided by Bernt Arne Ødegaard (2021b), which has collected data from OSE for a substantial period. We chose to use Ødegaard as a data provider as he has been granted permission by the OSE to publish data that goes further back and is more detailed than what is currently available to the public through both Euronext live, the operator of OSE and other applications such as Thomson Reuters Datastream. Turnover will be described a little more in detail under chapter 4.4.2.

As common practice when investigating asset prices, Ødegaard filters certain stocks out of his dataset to make the calculation of representat ive returns less problematic (French, 1992, as cited in Ødegaard, 2021a). One requirement is related to liquidity where the stocks must have a minimum of 20 trading days before they enter the sample. A second criteria is that stocks must have a minimum price of NOK 20 or higher to be included, as low valued stocks tend to have exaggerated returns. The last criterion is similar and requires total value outstanding to have a lower limit of NOK 1 million (Ødegaard, 2021a). The data for the OSESX have been collected from the operator of the OSE (Euronext, 2021). A full list of all the indices, along with descriptive data and the periods in which data has been collected for each index is presented in Table 4.4. The OBX include the 25 most traded stocks listed on OSE and is included to capture the broad market movements of the OSE. The OSESX consists of the 10% lowest capitalized shares and allows for investigation of the anomaly-sensitive small-cap companies. The sectorial indices are grouped up using the GICS standard (MSCI, 2021).

The stock returns are measured as logarithmic returns, as they are generally assumed to follow a log normal distribution (Stock & Watson, 2020). Furthermore, the returns are price returns on value weighted portfolios, which primarily means that dividends and interest is not included in the returns of a given stock. This is customary amongst papers on SAD and using the same form of returns allow us to more accurately compare the results with these previous papers (Kamstra et al., 2003; Bouman & Jacobsen, 2002).

The time-period we are studying for all indices, except the OSESX, Telecom and Utilities, are from 02.01.1990 to 30.12.2019. The accessible period for the OSESX were from 03.01.2000. For the Telecom and Utilities sectors available data is limited early in the time frame, therefore the period for Telecom starts at 06.05.1996 and Utilities 02.01.1996. Any movements that occurred during the period in which an industry is missing data will naturally not be captured by these industries, which could have some impact on the results for those industries. Uneven lengths in different returns-series have been the case in previous papers as well, but with no obvious correction have been made to adjust the data. Following previous papers tradition, we will not alter the data in any way, but the uneven length between indices should be kept in mind when interpreting results (Bouman & Jacobsen, 2002).

Table 4.4 Descriptive statistics of the included indices

Indices	Obs	Mean	Std. Dev.	Min	Max	Skew.	Kurt.
OBX *02.01.1990 – 30.12.2019*	7526	.028	1.438	-11.273	11.02	-.425	10.015
OSESX *03.01.2000 – 30.12.2019*	5016	.016	1.074	-7.525	9.769	-.74	9.543
Energy *02.01.1990 – 30.12.2019*	7526	.064	1.697	-10.08	11.996	-.062	7.211
Materials *02.01.1990 – 30.12.2019*	7445	.042	3.834	-66.9	74.215	.388	94.824
Industrials *02.01.1990 – 30.12.2019*	7526	.076	1.424	-9.715	10.774	-.189	8.231
Consumer discretionary *02.01.1990 – 30.12.2019*	7526	.095	2.043	-14.202	15.852	.19	9.77
Consumer staples *02.01.1990 – 30.12.2019*	7526	.078	1.522	-13.639	18.981	.175	13.274
Health *02.01.1990 – 30.12.2019*	7526	.07	1.746	-24.561	22.799	.556	20.45
Finance *02.01.1990 – 30.12.2019*	7526	.078	1.501	-13.204	14.329	.011	10.734
IT *02.01.1990 – 30.12.2019*	7526	.114	2.17	-28.679	24.074	-.363	15.566
Telecom *06.05.1996 – 30.12.2019*	5935	.048	2.271	-29.806	32.424	-.006	21.321
Utilities *02.01.1996 – 30.12.2019*	6020	.053	1.822	-14.278	18.826	.263	10.26

The table display descriptive statistics of the indices included in our study, with a daily percentage mean return ranging from 0.016 to 0.114 percent. Standard deviations range for most of the indices between 1.074 to 2.271 except for Basic materials which displays the most extreme standard deviation of 3.834, along with extreme minimum and maximum value compared to the other indices. There does not seem to be a clear pattern in the skewness in the industries of the OSE, as there is a mix of positive and negative values. Typically, it is expected that the skew is somewhat negative (Kamstra et al., 2003). Worth mentioning is that the OBX total return index has a negative skew of –0.425, which indicates that when considering the value of all indices there is a negative skew on the overall exchange. The kurtosis of the series is all strongly positive, which means that the index will likely experience extreme positive or negative returns on occasion.

The sectorial indices differ greatly in both number of firms in each index and average fraction of value over the time period examined. Some indices have only a couple of companies in them (Ødegaard (2021a). This stems from the fact that the Norwegian stock market contains a lot fewer companies compared to stock markets in most other nations. This is important to keep in mind when interpreting results. Though we might find significant results those results could be driven by only a handful of companies if there are few firms a given index. Should just a few new companies be added to the index, the results could change quite significantly. In addition, the fewer the firms, the more likely it is that factors unique to a specific firm will dilute the results on a coefficient.

4.4.2 Turnover data

The daily turnover is computed by dividing the number of shares traded on the OSE for a given day by the number of shares outstanding. Essentially the turnover measures the fraction of the OSEs total shares that switches hands on a given trading day. Ideally, we would have numbers on the turnover of each individual index. Having only the turnover on the entirety of OSE means that the interpretation of the TO and TO interaction variables will show us how the daily turnover on the OSE as a whole affects that index's returns.

The interpretation of the turnover coefficient is not entirely intuitive, as it is often quite large compared to the other coefficients. To find the turnover-related returns for a given trading day the turnover that day must be multiplied with the corresponding turnover coefficient. As seen from the descriptive statistics, the mean turnover on an average trading day is 0.003, meaning that 0.3% of all outstanding shares are traded on average each day. Multiplying this value with the TO-coefficient of any index will show us how great turnover-related returns was that day. The average OSE-turnover-related returns for the OBX would for instance be 0.161% (0.003 * 53.664 = 0.161).

Table 4.5 Descriptive statistics of Turnover

Variable	Obs.	Mean	Std. Dev.	Min	Max
Turnover	7526	0.003	0.002	0.001	0.025

4.4.3 Historical mean return on OSE indices

Graphs have been constructed for each index showing mean returns for each month over the years they have been active. The graphs start with the date of the autumn equinox for Norway, the point at which the SAD comes into effect, which is set to 21st of September. Though the graphs merely provide descriptive data, they could be interesting if for no other purpose than to identify potential seasonal patterns on the OSE.

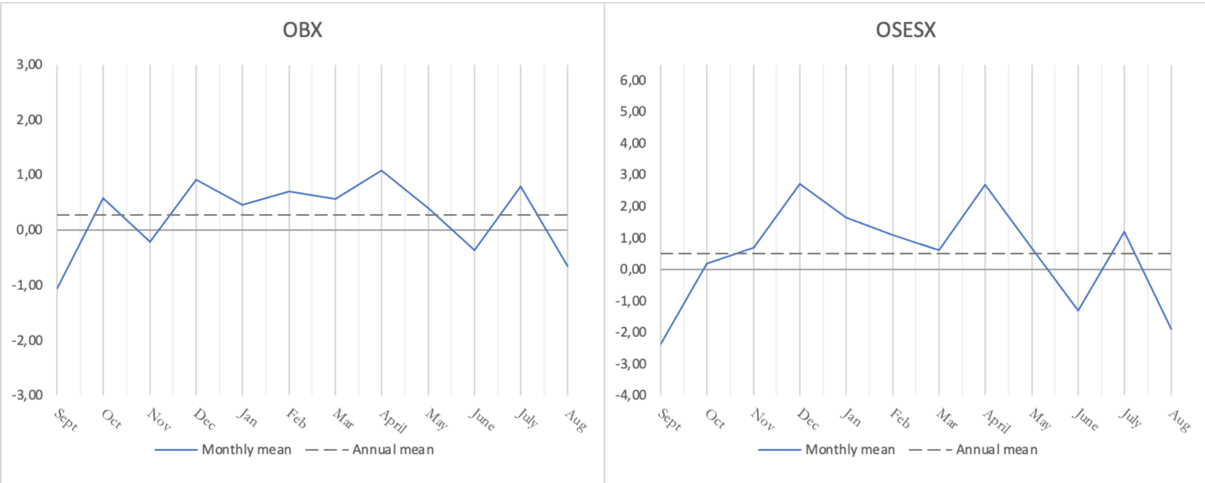

Figure 5. Mean return each month for the OBX Total return and the OSESX Small cap index.

Figure 5 displays the monthly mean returns for the OBX and the OSESX index, where returns on the OBX fluctuate close to the monthly mean in the summer months, below the mean in early fall, with an increase towards December and a peak in April. The OSESX displays a peak in December and April and with August and September as the months of lowest mean returns.

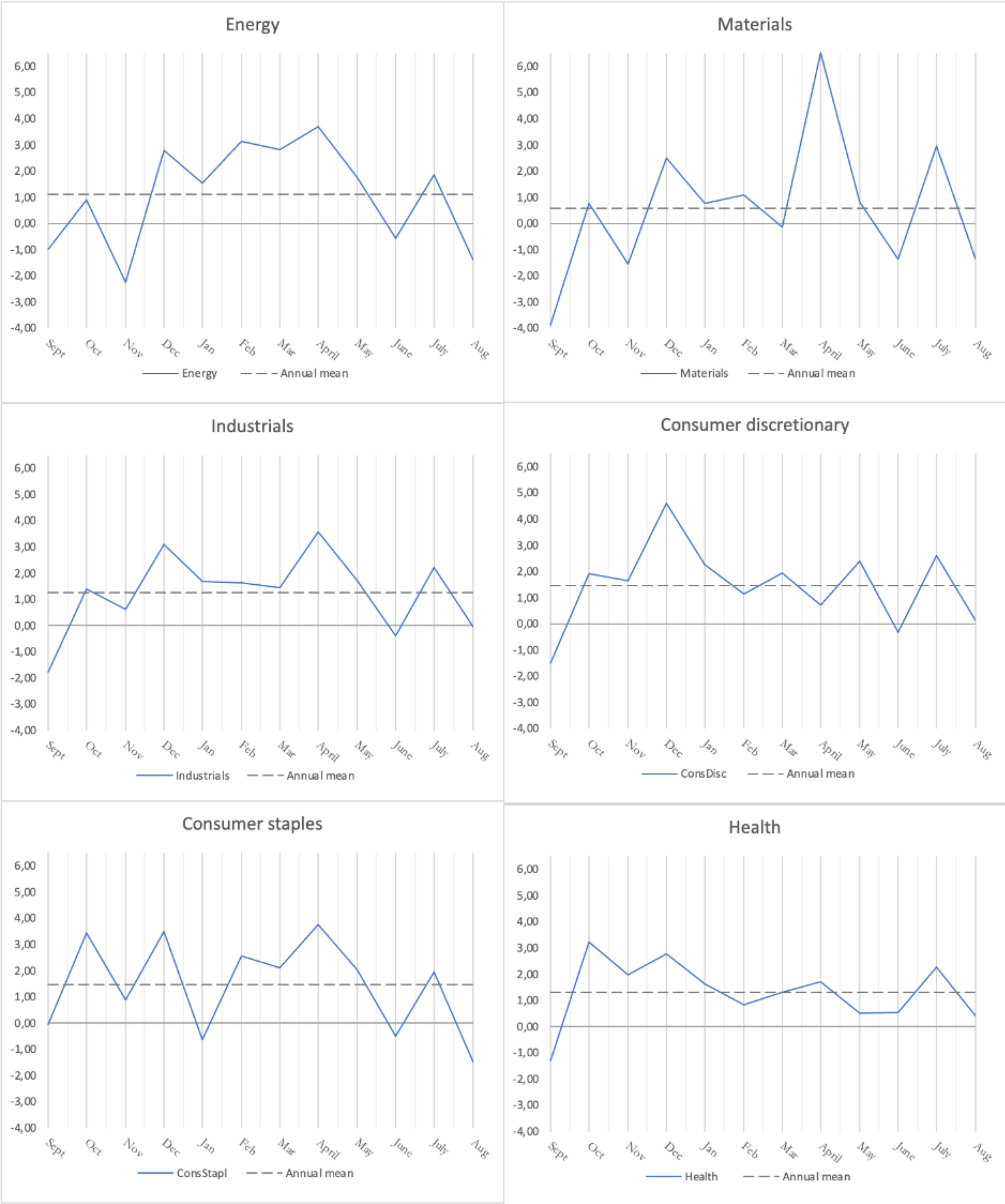

Figure 6. Mean return each month for the Energy, Materials, Industrials, Consumer discretionary, Consumer staples and Health sectorial indices.

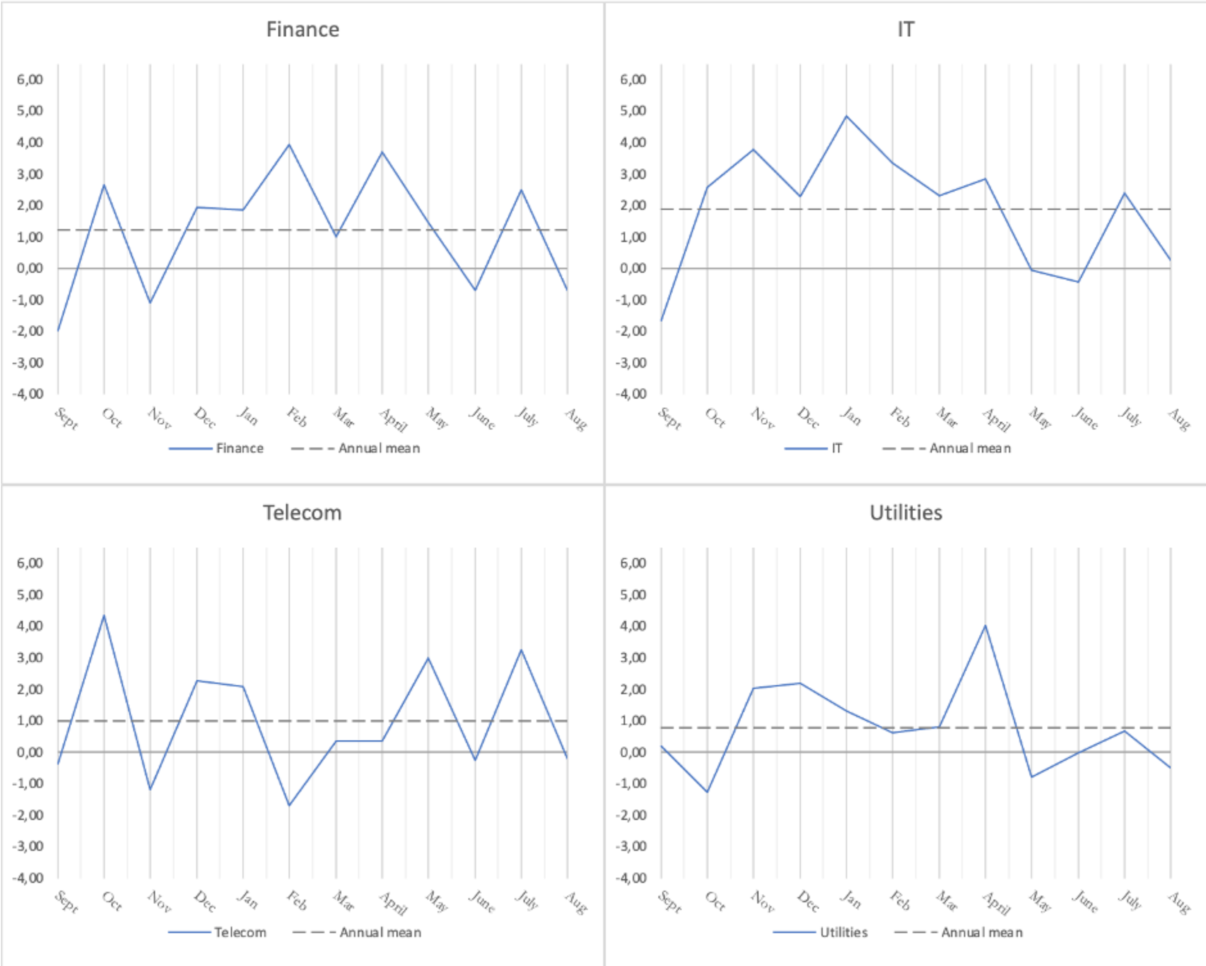

Figure 7. Mean return each month for Finance, IT, Telecommunications and Utilities sectorial indices

There are a couple of patterns that seem to be in common for some indices. We see that most indices have a return in August and September that is usually quite a bit below the mean return. October is usually a lot better, but there is a split between the indices. Energy, Materials, Industrials, Finance and Consumer staples indices all exhibit returns *below* the mean in most of the fall months, ranging from August through November. January is also a common month for returns to be above the mean as displayed by the Industrials, Consumer discretionary, IT and Finance sectors. However, the size of these returns are not as extreme as one might expect according to the January effect, especially when observing the OBX and OSESX. Though the returns vary a bit from index to index, most seem to have an at-the-mean or above-the-mean return for most of the winter period, ranging from December to April or May. One notable exception here being the Telecom index. Otherwise, indices Energy, Materials, Industrials, Finance, Telecom and Utilities all have a peak towards March and April. This is pretty much in line with the theory presented in *Winter Blues* (2003). The returns during the summer period tend to be below the mean in June while July often performs at the mean or higher.

5 Results

In this section, we present and discuss results from the models introduced in the method section. Chapter 5.1 and 5.2 present the results for our two respective hypotheses, while we investigate whether the results might have changed in significance over time in chapter 5.3. Chapter 5.4 explore various robustness tests before we present alternate explanations for our results in 5.5 and potential trading strategies in chapter 5.6.

5.1 Hypothesis 1 - Does the SAD affect returns on the OSE?

Assuming that the SAD exists in the OSE and follows the established literature, we expect that significant SAD-coefficients will be positive, and likewise the Fall-coefficients to be negative.

Table 5.1 SAD specification (Mod. 1)

$$r_t = \beta_0 + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{SAD} SAD_t + \beta_{Fall} D_t^{Fall} + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{Temp} Temp_t + \beta_{CloCov} CloCov_t + \beta_{Precip} Precip_t + \varepsilon_t$$

	OBX	OSESX	Energy	Materials	Indus trials	Cons Disc	Cons Stapl	Health	Finan	IT	Tele com	Utilities
SAD	0.005	0.027*	-0.007	0.057	0.023	0.037	-0.018	0.031	0.014	0.057**	0.043	0.015
	(0.016)	(0.014)	(0.018)	(0.044)	(0.016)	(0.023)	(0.017)	(0.020)	(0.016)	(0.024)	(0.036)	(0.022)
Fall	-0.082	-0.164**	-0.107	-0.224	-0.148*	-0.143	0.092	-0.125	-0.138	-0.275**	-0.202	-0.083
	(0.081)	(0.073)	(0.094)	(0.186)	(0.083)	(0.115)	(0.088)	(0.097)	(0.085)	(0.123)	(0.180)	(0.113)
$Return_{t-1}$	0.017	0.100***	0.025	-0.353***	0.042**	0.046**	0.016	0.015	0.047**	-0.000	-0.001	-0.140***
	(0.021)	(0.024)	(0.018)	(0.058)	(0.019)	(0.019)	(0.018)	(0.018)	(0.022)	(0.022)	(0.037)	(0.021)
$Return_{t-2}$	-0.028	0.073***	-0.034**	-0.071*	-0.011	0.013	-0.014	-0.005	-0.028	-0.037*	-0.038	-0.037**
	(0.022)	(0.022)	(0.017)	(0.042)	(0.020)	(0.019)	(0.018)	(0.018)	(0.020)	(0.021)	(0.030)	(0.018)
Monday	-0.067	0.228***	-0.082*	-0.094	-0.060	-0.067	-0.067	-0.143***	-0.091**	-0.078	0.084	-0.066
	(0.046)	(0.034)	(0.049)	(0.096)	(0.041)	(0.061)	(0.044)	(0.050)	(0.044)	(0.061)	(0.071)	(0.060)
Tax	0.354*	0.423**	0.149	-0.447	0.126	0.273	-0.241	-0.185	-0.118	-0.524*	0.279	-0.401**
	(0.190)	(0.168)	(0.217)	(0.510)	(0.169)	(0.271)	(0.171)	(0.219)	(0.170)	(0.313)	(0.261)	(0.202)
Temp	-0.006**	-0.003	-0.009***	-0.001	-0.003	-0.001	-0.009***	-0.000	-0.005**	-0.006*	0.002	-0.005
	(0.002)	(0.002)	(0.003)	(0.008)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)	(0.004)
Precip	0.003	-0.001	-0.001	-0.003	-0.001	0.004	-0.001	0.001	-0.000	-0.003	-0.010*	-0.001
	(0.003)	(0.003)	(0.004)	(0.008)	(0.003)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.005)
CloCov	-0.012	-0.019**	-0.007	0.000	-0.006	-0.018	-0.008	-0.000	0.005	-0.013	-0.009	0.003
	(0.008)	(0.007)	(0.009)	(0.021)	(0.008)	(0.011)	(0.008)	(0.010)	(0.008)	(0.012)	(0.014)	(0.011)
Const.	0.147***	0.084	0.227***	0.046	0.130**	0.161**	0.211***	0.076	0.116**	0.227***	0.055	0.095
	(0.051)	(0.051)	(0.064)	(0.170)	(0.053)	(0.076)	(0.057)	(0.067)	(0.053)	(0.080)	(0.095)	(0.077)
Obs.	7524	5014	7524	7442	7524	7524	7524	7524	7524	7524	5933	6018
Adj. R	0.003	0.030	0.003	0.112	0.002	0.003	0.002	0.001	0.004	0.003	0.001	0.019
F-stat.	2.424	10.788	3.089	4.679	1.817	2.152	2.343	1.487	2.476	2.678	1.239	6.219

Standard errors in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$
Returns are presented as daily log returns in percent. The regressions are estimated over the period of 02.01.1990 - 30.12.2019, except OSESX (04.01.2000), Utilities (02.01.1996) and Telecom (06.05.1996).
SAD is continuous variable capturing the effect of SAD (0, 6.43). *Fall* is a dummy variable capturing the asymmetry at winter solstice (Sept. 21st to Dec. 21st equals 1, otherwise 0). *Monday* is a dummy variable controlling for the weekend effect (1 on Mondays, 0 otherwise). *Tax* is a dummy variable controlling for the January effect (1 for the first five and the last trading day of the year, otherwise 0). *Temp* is a control variable measured in Celsius. *Precip* is a control variable measuring precipitation in millimeters. *CloCov* is a control variable measuring Cloud cover in octas, where 0 is clear sky, and 8 is complete cloud cover.

Results from table 5.1 show that neither the OBX total return index nor the OSESX small-cap index seem to have their returns significantly impacted by the SAD, showing no significance on their respective SAD-coefficients. Note however that the OSESX has significant coefficients for most independent variables, except for a couple of the weather-related variables and the SAD variable. This somewhat supports the theory presented in chapter 2.2, which suggests that anomalies tend to be particularly pronounced in small-cap companies. The SAD-anomaly however does not seem to be one of them. Amongst the sectorial indices, we find that only the IT-index has a significant SAD-coefficient on a 5% level. Further, only the OSESX and IT indices had a Fall-coefficient significant on the 5% level.

Though only the IT-index seems to be significantly impacted by the SAD, it follows exactly what is suggested in the SAD-theory established in *Winter Blues* (2003). The index is significant on both the SAD- and the Fall-coefficient, with positive and negative signs respectively. This suggest that the index's returns are not only affected by the SAD, but it has a *negative* impact in the fall and a *positive* impact in the winter.

The size and sign of the coefficients are quite similar to the ones found for the Swedish stock market in *Winter Blues* (2003), which has roughly the same latitude as OSE. The SAD-coefficient on the IT-index being 0.057 compared to the Swedish markets 0.028, and the fall-coefficient being -0.164 and -0.275 for the OSESX and IT indices respectively, compared to -0.113 for the Swedish market overall (Kamstra et al., 2003). Where the results are significant, they suggest that the SAD has not changed much in size for the latitude we examine, though results could of course be different on the Swedish market today.

5.2 Hypothesis 2 – Does snow cover affect SAD-related returns?

In the process of answering our second null-hypothesis, four separate regression models have been run as shown under chapter 3.2. The results of models 3 and 4 are presented in table 5.3, where we examine whether snow cover has any impact on returns in general. Table 5.4 show the results related to snow covers effect on SAD-related returns (models 5 and 7).

5.2.1 Does snow cover impact stock returns?

In panel A of table 5.2 we see that regressing only the SnoCov on returns suggest that as many as five indices have their returns reacting significantly on snow cover on a 5% level or stronger. All significant SnoCov coefficients are positive, suggesting that snow cover when significant have a positive relationship with stock returns on OSE. When including the non-SAD control variables in panel B however, the significance for all indices goes away. This indicates that it was not really snow itself, but some other parameter that caused the SnoCov variable to be significant.

Table 5.2 Link between snow and weather on OSE (Mod 3 & 4)

	OBX	OSESX	Energy	Materials	Indus trials	Cons Disc	Cons Stapl	Health	Finan	IT	Tele com	Utilities
Panel A: Step 1 – Snow cover on returns												
SnoCov	0.021**	0.023***	0.027**	0.007	0.014	0.004	0.011	0.020	0.021**	0.025*	0.018	0.036***
	(0.009)	(0.009)	(0.011)	(0.032)	(0.010)	(0.014)	(0.010)	(0.012)	(0.010)	(0.015)	(0.017)	(0.014)
Const.	0.006	-0.010	0.036	0.051	0.058***	0.085***	0.065***	0.049**	0.054***	0.093***	0.032	0.024
	(0.020)	(0.018)	(0.023)	(0.041)	(0.020)	(0.028)	(0.021)	(0.023)	(0.021)	(0.030)	(0.036)	(0.027)
Adj. R	0.001	0.020	0.002	0.113	0.002	0.002	0.000	0.000	0.003	0.001	0.001	0.020
F-stat.	2.489	13.152	4.014	13.030	2.488	2.256	0.854	1.117	3.809	1.940	1.011	17.214
Panel B: Step 2 – Snow cover and control variables												
SnoCov	0.005	0.016	0.008	-0.020	0.001	-0.017	-0.020	0.021	0.008	-0.010	0.022	0.033*
	(0.014)	(0.012)	(0.017)	(0.044)	(0.014)	(0.021)	(0.015)	(0.017)	(0.014)	(0.022)	(0.027)	(0.019)
Const.	0.124**	0.068	0.161**	0.158	0.141**	0.243***	0.232***	0.071	0.094	0.302***	0.056	0.042
	(0.058)	(0.055)	(0.072)	(0.151)	(0.059)	(0.087)	(0.065)	(0.070)	(0.060)	(0.092)	(0.106)	(0.080)
Adj. R	0.002	0.030	0.002	0.112	0.002	0.003	0.002	0.001	0.003	0.002	0.001	0.020
F-stat.	2.465	11.872	2.485	5.283	1.754	2.058	2.559	1.467	2.404	2.376	1.593	7.230
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	7524	5014	7524	7442	7524	7524	7524	7524	7524	7524	5933	6018

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Returns are presented as daily log returns in percent. The regressions are estimated over the period of 02.01.1990 - 30.12.2019, except OSESX (04.01.2000), Utilities (02.01.1996) and Telecom (06.05.1996).

Controls: Includes the variables of Monday, Tax, Temp, Precip and CloCov.

Monday is a dummy variable controlling for the weekend effect (1 on Mondays, 0 otherwise). *Tax* is a dummy variable controlling for the January effect (1 for the first five and the last trading day of the year, otherwise 0). *Temp* is a control variable measured in Celsius. *Precip* is a control variable measuring precipitation in millimeters. *CloCov* is a control variable measuring Cloud cover in octas, where 0 is clear sky, and 8 is complete cloud cover. SnoCov controls for the amount of snow covering the ground (0 is no cover, 4 is complete cover).

5.2.2 Does SAD/Fall change when controlling for snow cover?

Comparing the results from panel A in table 5.3 to the ones from table 5.1, we find that adding snow cover as a control variable to the original SAD-model, yields no difference in significance for the SAD-coefficient for the OBX. This suggest that the SAD's effect on returns is not impacted by snow cover for the broad market index for OSE. The SAD-coefficient for the OSESX index has changed and is now significant at a 5%-level. Suggesting that the SAD has a significant impact on returns for this index when controlled for snow cover. Again, the SAD-coefficient follows the expectations of being positive. Its size is also almost exactly the same as the SAD-effect found in the Swedish stock market with a value of 0.027 compared to Sweden's 0.028 (Kamstra et al. 2003). The OSESX having its returns significantly impacted by SAD after adding the snow cover variable, could indicate that there were some variations in weather that prevented the SAD from being significant for this index in model 1. For the sectorial indices, the IT index has its SAD-coefficient virtually unchanged in both size, sign and significance after adding the snow cover variable. This implies that snow cover has little to no impact on this index.

Otherwise, SnoCov seems to have no significant impact on return for any of the indices, with the SnoCov-coefficient being insignificant for all indices. Overall, it seems as if snow cover only has an impact on the OSESX when it comes to SAD-related returns.

In panel B we see that the two portfolios that did have a significant SAD-coefficient in panel A (OSESX and IT), no longer are significant after we have accounted for the interaction between SnoCov and SAD. The reason why no SAD coefficients are significant in panel B could be that the explanatory power of SAD has been reduced by including this many variables into the regression. In the end, the SAD/snow cover interaction coefficient is not significant for any of the indices, and we cannot confidently claim that snow cover has an impact on SAD-related returns.

Table 5.3 SAD specification including snow cover (Mod. 5) and interaction (Mod. 7)

	OBX	OSESX	Energy	Materials	Indus trials	Cons Disc	Cons Stapl	Health	Finan	IT	Tele com	Utilities
Panel A: Step 3 – Snow cover												
SAD	0.005	0.027**	-0.007	0.058	0.023	0.037	-0.018	0.031	0.014	0.057**	0.043	0.016
	(0.016)	(0.014)	(0.018)	(0.044)	(0.016)	(0.023)	(0.017)	(0.020)	(0.016)	(0.024)	(0.036)	(0.022)
Fall	-0.086	-0.152**	-0.119	-0.248	-0.155*	-0.163	0.069	-0.097	-0.141	-0.294**	-0.177	-0.044
	(0.084)	(0.075)	(0.097)	(0.201)	(0.086)	(0.118)	(0.091)	(0.101)	(0.087)	(0.129)	(0.191)	(0.116)
SnoCov	-0.003	0.012	-0.011	-0.021	-0.006	-0.018	-0.020	0.025	-0.003	-0.017	0.024	0.036*
	(0.015)	(0.013)	(0.018)	(0.045)	(0.015)	(0.022)	(0.016)	(0.018)	(0.015)	(0.023)	(0.029)	(0.021)
Const.	0.155**	0.057	0.251***	0.094	0.145**	0.202**	0.258***	0.017	0.122*	0.266***	0.000	0.011
	(0.062)	(0.062)	(0.078)	(0.170)	(0.063)	(0.093)	(0.068)	(0.075)	(0.063)	(0.099)	(0.112)	(0.091)
Adj. R	0.002	0.030	0.003	0.112	0.002	0.003	0.002	0.001	0.004	0.003	0.001	0.020
F-stat.	2.182	9.886	2.802	4.277	1.637	2.017	2.255	1.661	2.230	2.416	1.368	5.814
Panel B: Step 4 – Snow cover and interaction term												
SAD	-0.008	0.018	-0.023	0.044	0.008	0.042	-0.027	0.043*	0.011	0.043	0.022	0.015
	(0.018)	(0.016)	(0.022)	(0.043)	(0.018)	(0.027)	(0.019)	(0.022)	(0.019)	(0.028)	(0.043)	(0.025)
Fall	-0.060	-0.134*	-0.089	-0.220	-0.125	-0.173	0.086	-0.120	-0.134	-0.266**	-0.133	-0.042
	(0.086)	(0.076)	(0.100)	(0.193)	(0.087)	(0.122)	(0.092)	(0.102)	(0.088)	(0.133)	(0.200)	(0.118)
SnoCov	-0.022	-0.002	-0.033	-0.041	-0.029	-0.011	-0.033	0.043*	-0.007	-0.037	-0.008	0.035
	(0.018)	(0.018)	(0.022)	(0.072)	(0.019)	(0.027)	(0.020)	(0.025)	(0.020)	(0.029)	(0.034)	(0.028)
SAD_SC	0.007	0.005	0.008	0.007	0.008*	-0.003	0.004	-0.006	0.002	0.007	0.011	0.001
	(0.005)	(0.004)	(0.005)	(0.015)	(0.004)	(0.007)	(0.005)	(0.006)	(0.005)	(0.007)	(0.008)	(0.006)
Const.	0.187***	0.079	0.290***	0.128	0.183***	0.190**	0.279***	-0.012	0.130*	0.300***	0.053	0.014
	(0.063)	(0.066)	(0.081)	(0.176)	(0.066)	(0.097)	(0.070)	(0.078)	(0.067)	(0.100)	(0.116)	(0.097)
Adj. R	0.003	0.030	0.004	0.112	0.003	0.003	0.002	0.001	0.004	0.003	0.002	0.020
F-stat.	2.226	9.263	2.741	3.924	1.816	1.861	2.271	1.598	2.030	2.301	1.466	5.285
Obs.	7524	5014	7524	7442	7524	7524	7524	7524	7524	7524	5933	6018
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Returns are presented as daily log returns in percent. The regressions are estimated over the period of 02.01.1990 - 30.12.2019, except OSESX (04.01.2000), Utilities (02.01.1996) and Telecom (06.05.1996).

Controls: Includes the variables of Monday, Tax, Temp, Precip and CloCov. *SAD* is a continuous variable capturing the effect of SAD (0, 6.43). *Fall* is a dummy variable capturing the asymmetry at winter solstice (Sept. 21st to Dec. 21st equals 1, otherwise 0). *Monday* is a dummy variable controlling for the weekend effect (1 on Mondays, 0 otherwise). *Tax* is a dummy variable controlling for the January effect (1 for the first five and the last trading day of the year, otherwise 0). *Temp* is a control variable measured in Celsius. *Precip* is a control variable measuring precipitation in millimeters. *CloCov* is a control variable measuring Cloud cover in octas, where 0 is clear sky, and 8 is complete cloud cover. SnoCov controls for the amount of snow covering the ground (0 is no cover, 4 is complete cover).

5.3 Investigating the resilience of SAD - The SAD before and after Winter Blues (2003)

Though it seems like only the IT index is significantly impacted by the SAD, and snow cover appears to have no impact on the SAD, it could be that the impact of both SAD and snow cover has changed in significance over time. Exploring our base models before and after the publication of the *Winter Blues* (2003) paper, we got the following results:

5.3.1 Resilience of Model 1 – The original SAD-model

Table 5.4 SAD specification (Mod. 1) – Resilience test

Panel A: SAD regression 02.01.1990 – 30.12.2002	OBX	OSESX	Energy	Materials	Indus trials	Cons Disc	Cons Stapl	Health	Finan	IT	Tele com	Utilities
SAD	0.003	-0.012	-0.003	0.011	0.004	0.043	-0.020	0.071^{**}	0.027	0.086^{**}	0.116	0.008
	(0.023)	(0.043)	(0.028)	(0.030)	(0.023)	(0.036)	(0.026)	(0.036)	(0.023)	(0.038)	(0.108)	(0.049)
Fall	-0.065	0.019	-0.178	-0.119	-0.138	-0.224	0.180	-0.284^{*}	-0.159	-0.377^{**}	-0.601	0.103
	(0.119)	(0.224)	(0.140)	(0.150)	(0.118)	(0.177)	(0.135)	(0.169)	(0.118)	(0.189)	(0.514)	(0.246)
Const.	0.153^{**}	0.099	0.263^{***}	0.255^{***}	0.177^{**}	0.314^{***}	0.238^{***}	0.035	0.132^{**}	0.313^{**}	0.067	-0.028
	(0.070)	(0.143)	(0.093)	(0.093)	(0.071)	(0.114)	(0.081)	(0.123)	(0.067)	(0.127)	(0.246)	(0.168)
Obs.	3256	746	3256	3256	3256	3256	3256	3256	3256	3256	1665	1750
Adj. R	0.011	0.039	0.013	0.014	0.012	0.009	0.008	0.005	0.010	0.004	0.011	0.052
F-stat.	3.072	3.883	3.820	4.315	3.438	2.944	3.208	2.339	2.739	2.327	1.513	6.746
Panel B: SAD regression 02.01.2003 – 30.12.2019												
SAD	0.003	0.033^{**}	-0.013	0.093	0.036^{*}	0.025	-0.016	-0.005	0.001	0.031	0.007	0.015
	(0.021)	(0.014)	(0.024)	(0.074)	(0.022)	(0.030)	(0.022)	(0.020)	(0.023)	(0.031)	(0.024)	(0.024)
Fall	-0.079	-0.194^{**}	-0.034	-0.278	-0.145	-0.042	0.014	0.025	-0.106	-0.174	0.003	-0.132
	(0.112)	(0.077)	(0.126)	(0.319)	(0.116)	(0.149)	(0.116)	(0.106)	(0.123)	(0.162)	(0.127)	(0.120)
Const.	0.153^{**}	0.079	0.200^{**}	-0.177	0.098	0.040	0.200^{**}	0.110	0.104	0.153	0.040	0.113
	(0.072)	(0.055)	(0.090)	(0.297)	(0.077)	(0.101)	(0.080)	(0.067)	(0.081)	(0.102)	(0.091)	(0.082)
Obs.	4268	4268	4268	4186	4268	4268	4268	4268	4268	4268	4268	4268
Adj. R	0.001	0.028	0.001	0.145	-0.001	0.001	0.002	0.004	0.002	0.003	0.007	0.007
F-stat.	1.277	8.520	1.147	5.166	0.608	1.088	1.299	2.201	1.193	1.232	2.107	2.631
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$
Returns are presented as daily log returns in percent. The regressions are estimated over the period of 02.01.1990 - 30.12.2019, except OSESX (04.01.2000), Utilities (02.01.1996) and Telecom (06.05.1996).
Controls: Includes the variables of Monday, Tax, Temp, Precip and CloCov.
SAD is continuous variable capturing the effect of SAD (0, 6.43). *Fall* is a dummy variable capturing the asymmetry at winter solstice (Sept. 21st to Dec. 21st equals 1, otherwise 0). *Monday* is a dummy variable controlling for the weekend effect (1 on Mondays, 0 otherwise). *Tax* is a dummy variable controlling for the January effect (1 for the first five and the last trading day of the year, otherwise 0). *Temp* is a control variable measured in Celsius. *Precip* is a control variable measuring precipitation in millimeters. *CloCov* is a control variable measuring Cloud cover in octas, where 0 is clear sky, and 8 is complete cloud cover. SnoCov controls for the amount of snow covering the ground (0 is no cover, 4 is complete cover).

From the results in table 5.4 we find that the OBX has no significant SAD-coefficients in either the pre-2003 sample, nor the post-2003 sample. The OSESX has no significant coefficients for either SAD or Fall in the pre-2003 period, but both are significant at a 5%-level in the post-2003 period. For the sectorial indices we find that during the time period 02.01.1990 to 02.01.2003 the Health and IT indices show positive and significant SAD-coefficients. The Fall variable is negative and significant at the 5% level for the IT index. In the post-2003 period, the two significant pre-period indices lose their significance on the SAD-coefficient.

The results from our base model are somewhat mixed. With no significance in the variables of the OBX it does not seem that there's been a change in the SAD-effect on the OSE at large between the two periods studied. However, the OSESX seems to have become *more* responsive to the SAD over time, which is counter to what one would expect if the market was truly efficient. The returns of sectorial indices Health and IT on the other hand, seems to have been affected by the SAD in the past, but lost their significance in the period after *Winter Blues* (2003) was released.

5.3.2 Resilience of Model 5 – Introducing the Snow cover variable to the original model

Table 5.5 SAD specification with Snow cover (Mod. 5) – Resilience test

	OBX	OSESX	Energy	Materials	Indus trials	Cons Disc	Cons Stapl	Health	Finan	IT	Tele com	Utilities
Panel A: SAD regression with *Snow cover* for the time period 02.01.1990 – 30.12.2002												
SAD	0.003	-0.013	-0.003	0.012	0.004	0.045	-0.018	0.069*	0.029	0.087**	0.113	0.009
	(0.024)	(0.043)	(0.029)	(0.030)	(0.024)	(0.036)	(0.026)	(0.037)	(0.023)	(0.038)	(0.109)	(0.049)
Fall	-0.060	0.014	-0.184	-0.136	-0.142	-0.266	0.138	-0.231	-0.194*	-0.397**	-0.500	0.044
	(0.122)	(0.226)	(0.144)	(0.152)	(0.121)	(0.180)	(0.137)	(0.179)	(0.118)	(0.196)	(0.549)	(0.255)
SnoCov	0.004	-0.008	-0.006	-0.014	-0.003	-0.035	-0.035	0.044	-0.029*	-0.017	0.096	-0.052
	(0.019)	(0.038)	(0.025)	(0.026)	(0.020)	(0.031)	(0.022)	(0.032)	(0.018)	(0.036)	(0.072)	(0.045)
Const.	0.144*	0.116	0.275**	0.286***	0.185**	0.391***	0.316***	-0.063	0.196**	0.350**	-0.136	0.087
	(0.082)	(0.145)	(0.109)	(0.110)	(0.083)	(0.137)	(0.096)	(0.131)	(0.078)	(0.150)	(0.261)	(0.192)
Obs.	3256	746	3256	3256	3256	3256	3256	3256	3256	3256	1665	1750
Adj. R	0.010	0.038	0.013	0.014	0.012	0.009	0.009	0.005	0.010	0.003	0.012	0.052
F-stat.	2.766	3.503	3.461	3.912	3.099	2.861	3.114	2.537	2.911	2.161	1.964	6.423
Panel B: SAD regression with *Snow cover* for the time period 02.01.2003 – 30.12.2019												
SAD	0.003	0.034**	-0.014	0.092	0.036*	0.025	-0.016	-0.005	0.002	0.030	0.007	0.018
	(0.021)	(0.014)	(0.024)	(0.073)	(0.022)	(0.029)	(0.022)	(0.020)	(0.023)	(0.031)	(0.024)	(0.024)
Fall	-0.090	-0.179**	-0.051	-0.307	-0.153	-0.045	0.004	0.028	-0.088	-0.195	-0.002	-0.058
	(0.117)	(0.078)	(0.132)	(0.344)	(0.121)	(0.156)	(0.120)	(0.109)	(0.128)	(0.170)	(0.130)	(0.123)
SnoCov	-0.010	0.014	-0.016	-0.027	-0.007	-0.002	-0.009	0.002	0.018	-0.020	-0.005	0.070***
	(0.022)	(0.014)	(0.025)	(0.078)	(0.021)	(0.030)	(0.022)	(0.020)	(0.023)	(0.031)	(0.026)	(0.022)
Const.	0.176*	0.045	0.239**	-0.113	0.115	0.046	0.222**	0.104	0.063	0.201	0.051	-0.053
	(0.091)	(0.068)	(0.111)	(0.298)	(0.095)	(0.128)	(0.096)	(0.082)	(0.098)	(0.131)	(0.114)	(0.097)
Obs.	4268	4268	4268	4186	4268	4268	4268	4268	4268	4268	4268	4268
Adj. R	0.001	0.028	0.001	0.145	-0.001	0.001	0.002	0.003	0.002	0.003	0.007	0.010
F-stat.	1.162	7.804	1.068	4.782	0.548	0.980	1.185	1.984	1.148	1.117	1.902	3.235
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
$^{*} p < 0.10$, $^{**} p < 0.05$, $^{***} p < 0.01$
Returns are presented as daily log returns in percent. The regressions are estimated over the period of 02.01.1990 - 30.12.2019, except OSESX (04.01.2000), Utilities (02.01.1996) and Telecom (06.05.1996).
Controls: Includes the variables of Monday, Tax, Temp, Precip and CloCov.
SAD is continuous variable capturing the effect of SAD (0, 6.43). *Fall* is a dummy variable capturing the asymmetry at winter solstice (Sept. 21st to Dec. 21st equals 1, otherwise 0). *Monday* is a dummy variable controlling for the weekend effect (1 on Mondays, 0 otherwise). *Tax* is a dummy variable controlling for the January effect (1 for the first five and the last trading day of the year, otherwise 0). *Temp* is a control variable measured in Celsius. *Precip* is a control variable measuring precipitation in millimeters. *CloCov* is a control variable measuring Cloud cover in octas, where 0 is clear sky, and 8 is complete cloud cover. SnoCov controls for the amount of snow covering the ground (0 is no cover, 4 is complete cover).

Introducing the snow cover variable result in virtually no change to significance, sign or size in any of the indices when comparing results in table 5.5 to table 5.4. The OBX is still not significant in either period. The OSESX displays the same change in significance over time in both tables, with small changes in the values of the coefficients. For the sectorial indices, only the IT-index is significant, and drops from being significant on a 5%-level in the pre-2003 period, to being insignificant in the post-2003 period. None of the indices have a significant coefficient for snow cover in the pre-period while only the Utilities index is significant in the post period.

5.3.3 Resilience of Model 7 – Adding Snow cover and interaction term to the original model

Table 5.6 SAD specification with Snow cover and interaction (Mod. 7)

	OBX	OSESX	Energy	Materials	Indus trials	Cons Disc	Cons Stapl	Health	Finan	IT	Tele com	Utilities
Panel A: SAD regression with *Snow cover* for the time period 02.01.1990 – 30.12.2002												
SAD	-0.014	-0.027	-0.022	-0.015	-0.009	0.064	-0.036	0.099**	0.029	0.091*	0.090	0.029
	(0.028)	(0.049)	(0.034)	(0.035)	(0.027)	(0.044)	(0.030)	(0.041)	(0.027)	(0.047)	(0.130)	(0.058)
Fall	-0.030	0.040	-0.149	-0.088	-0.118	-0.301	0.171	-0.286	-0.194	-0.405*	-0.456	0.004
	(0.125)	(0.232)	(0.147)	(0.155)	(0.123)	(0.187)	(0.138)	(0.180)	(0.120)	(0.207)	(0.581)	(0.261)
SnoCov	-0.019	-0.028	-0.033	-0.052	-0.022	-0.008	-0.061**	0.086*	-0.029	-0.011	0.062	-0.026
	(0.024)	(0.061)	(0.033)	(0.032)	(0.025)	(0.038)	(0.029)	(0.049)	(0.022)	(0.045)	(0.086)	(0.061)
SAD_SC	0.008	0.007	0.009	0.013	0.006	-0.009	0.009	-0.014	0.000	-0.002	0.012	-0.009
	(0.006)	(0.013)	(0.008)	(0.008)	(0.006)	(0.010)	(0.007)	(0.010)	(0.006)	(0.013)	(0.022)	(0.015)
Const.	0.185**	0.152	0.323***	0.351***	0.217**	0.345**	0.360***	-0.136	0.196**	0.340**	-0.084	0.043
	(0.086)	(0.167)	(0.117)	(0.116)	(0.088)	(0.144)	(0.101)	(0.139)	(0.083)	(0.155)	(0.280)	(0.212)
Obs.	3256	746	3256	3256	3256	3256	3256	3256	3256	3256	1665	1750
Adj. R	0.010	0.037	0.013	0.014	0.012	0.009	0.009	0.005	0.010	0.003	0.011	0.052
F-stat.	2.672	3.179	3.278	3.781	2.920	2.675	3.116	2.408	2.645	1.978	1.884	5.927
Panel B: SAD regression with *Snow cover* for the time period 02.01.2003 – 30.12.2019												
SAD	-0.008	0.026	-0.027	0.098	0.017	0.023	-0.017	-0.004	-0.002	0.007	-0.011	0.011
	(0.025)	(0.016)	(0.028)	(0.071)	(0.024)	(0.034)	(0.025)	(0.023)	(0.027)	(0.035)	(0.028)	(0.026)
Fall	-0.068	-0.162**	-0.025	-0.320	-0.116	-0.041	0.006	0.026	-0.080	-0.149	0.035	-0.045
	(0.121)	(0.079)	(0.136)	(0.329)	(0.122)	(0.160)	(0.122)	(0.111)	(0.130)	(0.173)	(0.133)	(0.125)
SnoCov	-0.026	0.002	-0.035	-0.019	-0.034	-0.005	-0.011	0.004	0.012	-0.053	-0.030	0.060**
	(0.026)	(0.019)	(0.030)	(0.120)	(0.027)	(0.039)	(0.029)	(0.025)	(0.030)	(0.037)	(0.033)	(0.029)
SAD_SC	0.006	0.004	0.007	-0.003	0.010	0.001	0.001	-0.001	0.002	0.012	0.009	0.004
	(0.007)	(0.004)	(0.008)	(0.024)	(0.006)	(0.009)	(0.006)	(0.006)	(0.007)	(0.008)	(0.008)	(0.007)
Const.	0.203**	0.066	0.270**	-0.127	0.160*	0.050	0.224**	0.102	0.073	0.257*	0.094	-0.036
	(0.092)	(0.072)	(0.113)	(0.303)	(0.096)	(0.132)	(0.097)	(0.083)	(0.102)	(0.131)	(0.116)	(0.103)
Obs.	4268	4268	4268	4186	4268	4268	4268	4268	4268	4268	4268	4268
Adj. R	0.001	0.028	0.001	0.145	-0.001	0.001	0.001	0.003	0.002	0.003	0.007	0.009
F-stat.	1.142	7.441	1.022	4.502	0.736	0.891	1.094	1.805	1.046	1.305	1.892	3.033
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$
Returns are presented as daily log returns in percent. The regressions are estimated over the period of 02.01.1990 - 30.12.2019, except OSESX (04.01.2000), Utilities (02.01.1996) and Telecom (06.05.1996).
Controls: Includes the variables of Monday, Tax, Temp, Precip and CloCov.
SAD is continuous variable capturing the effect of SAD (0, 6.43). *Fall* is a dummy variable capturing the asymmetry at winter solstice (Sept. 21st to Dec. 21st equals 1, otherwise 0). *Monday* is a dummy variable controlling for the weekend effect (1 on Mondays, 0 otherwise). *Tax* is a dummy variable controlling for the January effect (1 for the first five and the last trading day of the year, otherwise 0). *Temp* is a control variable measured in Celsius. *Precip* is a control variable measuring precipitation in millimeters. *CloCov* is a control variable measuring Cloud cover in octas, where 0 is clear sky, and 8 is complete cloud cover. SnoCov controls for the amount of snow covering the ground (0 is no cover, 4 is complete cover).

Improving on the model in table 5.5 by introducing the interaction variable between snow cover and the SAD, table 5.6 present some minor changes in significance and size of coefficients. The SAD and Fall variable for the OBX still displays no significance, however the SAD variables of the OSESX are now non-significant in both periods. As addressed in chapter 5.2.2, this might be due to the added variable absorbing patterns in variation that would otherwise show up in the SAD-coefficient. The fall-coefficient is however significant in the post-2003 period, suggesting that returns in the fall are significantly negative for the small cap index. For the sectorial indices only the Health index is significant in the pre-2003 period, but is not significant in the post-2003 period. In both periods, the interaction variable is insignificant for all indices.

5.3.4 Summary

The results of the regressions on the pre-2003 sample and post-2003 sample do not provide a clear indication on the presence of SAD in the market. The SAD coefficient of the OBX is not significant in any of the specifications for any period. For the OSESX, contrary to our expectations the effect of SAD seems to be significant in the second time-period and non-significant in the first. Suggesting that if the SAD is still in effect, it is most likely to be found in the OSESX in the post-2003 period. For the sectorial indices, all of the indices that have their returns react to the SAD were found in the first time period. This supports our expectations that the presence of SAD may diminished over time.

5.4 Robustness checks

Based on our results so far, we have not found much evidence suggesting that returns on OSE is affected by a SAD-effect. To check the robustness of our results, we run some extra statistical tests and explore alternative explanations that may be behind them.

5.4.1 The Onset/Recovery variable – An alternative measure of the SAD

While the original SAD model as presented *in Winter Blues* (2003) is the most commonly used way to measure SAD, improvements to the model have been suggested. Below we present the results from testing the same hypotheses as done under chapter 5.1 and 5.2, using a similar model with the only exception being that the SAD and Fall variables are replaced with the OR-variable. Testing our first hypothesis using the OR-model, we got the following results:

Table 5.7 OR specification (Mod. 2)

$$r_t = \beta_0 + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \beta_{OR} OR_t + \beta_{Monday} D_t^{Monday} + \beta_{Tax} D_t^{Tax} + \beta_{Temp} Temp_t + \beta_{CloCov} CloCov_t + \beta_{Precip} Precip_t + \varepsilon_t$$

	OBX	OSESX	Energy	Materials	Indus trials	Cons Disc	Cons Stapl	Health	Finan	IT	Tele com	Utilities
OR	-0.106*	-0.068	-0.148**	-0.163	-0.080	-0.033	-0.012	0.007	-0.104*	0.009	0.063	-0.083
	(0.060)	(0.054)	(0.070)	(0.162)	(0.060)	(0.083)	(0.063)	(0.073)	(0.063)	(0.089)	(0.104)	(0.082)
$Return_{t-1}$	0.017	0.101***	0.026	-0.353***	0.042**	0.047**	0.016	0.015	0.047**	0.000	-0.000	-0.140***
	(0.021)	(0.024)	(0.018)	(0.058)	(0.019)	(0.019)	(0.018)	(0.018)	(0.022)	(0.022)	(0.037)	(0.021)
$Return_{t-2}$	-0.028	0.074***	-0.034**	-0.071*	-0.011	0.014	-0.014	-0.005	-0.028	-0.037*	-0.038	-0.037**
	(0.022)	(0.022)	(0.017)	(0.042)	(0.020)	(0.019)	(0.018)	(0.018)	(0.020)	(0.021)	(0.030)	(0.018)
Monday	-0.067	0.229***	-0.083*	-0.092	-0.059	-0.067	-0.067	-0.142***	-0.091**	-0.077	0.085	-0.066
	(0.046)	(0.034)	(0.049)	(0.096)	(0.041)	(0.061)	(0.044)	(0.050)	(0.044)	(0.061)	(0.071)	(0.060)
Tax	0.404**	0.525***	0.201	-0.271	0.221	0.377	-0.298*	-0.100	-0.034	-0.349	0.403*	-0.341*
	(0.184)	(0.162)	(0.210)	(0.501)	(0.161)	(0.264)	(0.163)	(0.212)	(0.163)	(0.306)	(0.236)	(0.192)
Temp	-0.004*	-0.003	-0.005*	-0.004	-0.003	-0.003	-0.007***	-0.003	-0.004*	-0.011***	-0.001	-0.005
	(0.002)	(0.002)	(0.003)	(0.006)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)
Precip	0.003	-0.000	-0.001	-0.002	-0.001	0.004	-0.001	0.001	0.000	-0.003	-0.010*	-0.001
	(0.003)	(0.003)	(0.004)	(0.008)	(0.003)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.005)
CloCov	-0.011	-0.018**	-0.008	0.003	-0.005	-0.017	-0.008	0.000	0.005	-0.012	-0.008	0.004
	(0.008)	(0.007)	(0.009)	(0.021)	(0.008)	(0.011)	(0.008)	(0.010)	(0.008)	(0.012)	(0.014)	(0.011)
Const.	0.119**	0.088*	0.156**	0.095	0.131**	0.204***	0.192***	0.114*	0.094*	0.284***	0.106	0.094
	(0.049)	(0.049)	(0.062)	(0.141)	(0.051)	(0.073)	(0.055)	(0.062)	(0.051)	(0.078)	(0.090)	(0.071)
Obs.	7524	5014	7524	7442	7524	7524	7524	7524	7524	7524	5933	6018
Adj. R	0.003	0.030	0.003	0.112	0.002	0.003	0.002	0.000	0.004	0.002	0.001	0.020
F-stat.	2.803	11.749	3.081	5.588	1.929	1.938	2.444	1.303	2.709	2.373	1.335	7.171

Standard errors in parentheses.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Returns are presented as daily log returns in percent. The regressions are estimated over the period of 02.01.1990 – 30.12.2019, except OSESX (04.01.2000), Utilities (02.01.1996) and Telecom (06.05.1996).

OR expresses the proportion of people who suffer from SAD (-0,63 to 0,63). *Monday* is a dummy variable controlling for the weekend effect (1 on Mondays, 0 otherwise). *Tax* is a dummy variable controlling for the January effect (1 for the first five and the last trading day of the year, otherwise 0). *Temp* is a control variable measured in Celsius. *Precip* is a control variable measuring precipitation in millimeters. *CloCov* is a control variable measuring Cloud cover in octas, where 0 is clear sky, and 8 is complete cloud cover.

Similar to the SAD-model (table 5.1), the OR-model show no signs of the returns of either the OBX or the OSESX being significantly affected by the SAD. Of the sectorial indices, only the Energy index has its returns significantly impacted by the SAD on a 5% level. All other indices must keep the null-hypothesis of SAD not affecting returns. The one significant OR-variable is also following the expectation in that it is negative.

Further investigating the second hypothesis with the OR-model, we got the results presented in table 5.8:

Table 5.8 OR specification and Snow cover (Mod. 6) and interaction (Mod. 8)

Panel A: Step 3 – Snow cover												
	OBX	OSESX	Energy	Materials	Indus trials	Cons Disc	Cons Stapl	Health	Finan	IT	Tele com	Utilities
OR	-0.110*	-0.052	-0.153**	-0.212	-0.088	-0.063	-0.043	0.040	-0.104	-0.005	0.104	-0.042
	(0.061)	(0.056)	(0.072)	(0.151)	(0.061)	(0.086)	(0.064)	(0.072)	(0.065)	(0.092)	(0.105)	(0.084)
SnoCov	-0.003	0.012	-0.003	-0.036	-0.006	-0.022	-0.023	0.024	-0.000	-0.010	0.030	0.030
	(0.014)	(0.013)	(0.017)	(0.042)	(0.014)	(0.021)	(0.015)	(0.017)	(0.015)	(0.022)	(0.027)	(0.020)
Const.	0.124**	0.068	0.162**	0.159	0.141**	0.243***	0.233***	0.071	0.094	0.302***	0.055	0.042
	(0.058)	(0.055)	(0.072)	(0.151)	(0.059)	(0.087)	(0.065)	(0.070)	(0.060)	(0.092)	(0.106)	(0.080)
Adj. R	0.003	0.030	0.003	0.112	0.002	0.003	0.002	0.001	0.004	0.002	0.001	0.020
F-stat.	2.497	10.625	2.741	4.999	1.725	1.834	2.332	1.398	2.408	2.112	1.482	6.486
Panel B: Step 4 – Snow cover and Interaction term												
OR	-0.156**	-0.116*	-0.183**	-0.343**	-0.160**	-0.063	-0.050	0.032	-0.151**	-0.115	0.069	-0.079
	(0.071)	(0.064)	(0.084)	(0.153)	(0.071)	(0.100)	(0.075)	(0.081)	(0.076)	(0.106)	(0.121)	(0.096)
SnoCov	0.007	0.027*	0.003	-0.006	0.011	-0.022	-0.021	0.026	0.011	0.015	0.038	0.039*
	(0.016)	(0.014)	(0.020)	(0.040)	(0.016)	(0.024)	(0.017)	(0.018)	(0.017)	(0.026)	(0.030)	(0.023)
OR_SC	0.056	0.080**	0.037	0.161	0.089**	0.001	0.009	0.009	0.057	0.135**	0.044	0.045
	(0.039)	(0.035)	(0.046)	(0.154)	(0.039)	(0.057)	(0.042)	(0.050)	(0.041)	(0.060)	(0.068)	(0.056)
Const.	0.125**	0.070	0.162**	0.161	0.143**	0.243***	0.233***	0.071	0.095	0.304***	0.055	0.043
	(0.058)	(0.055)	(0.072)	(0.151)	(0.059)	(0.087)	(0.065)	(0.070)	(0.060)	(0.092)	(0.106)	(0.080)
Adj. R	0.003	0.031	0.003	0.113	0.003	0.002	0.002	0.000	0.004	0.003	0.001	0.020
F-stat.	2.398	10.133	2.506	4.525	1.973	1.666	2.114	1.276	2.292	2.368	1.373	5.893
Obs.	7524	5014	7524	7442	7524	7524	7524	7524	7524	7524	5933	6018
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Returns are presented as daily log returns in percent. The regressions are estimated over the period of 02.01.1990 - 30.12.2019, except OSESX (04.01.2000), Utilities (02.01.1996) and Telecom (06.05.1996).

Controls: Includes the variables of Monday, Tax, Temp, Precip and CloCov.

OR expresses the proportion of people who suffer from SAD (-0,63 to 0,63). *Monday* is a dummy variable controlling for the weekend effect (1 on Mondays, 0 otherwise). *Tax* is a dummy variable controlling for the January effect (1 for the first five and the last trading day of the year, otherwise 0). *Temp* is a control variable measured in Celsius. *Precip* is a control variable measuring precipitation in millimeters. *CloCov* is a control variable measuring Cloud cover in octas, where 0 is clear sky, and 8 is complete cloud cover. SnoCov controls for the amount of snow covering the ground (0 is no cover, 4 is complete cover).

Using the OR-model we find about the same results as we got using the standard SAD-model in table 5.3. Adding snow cover to the original OR-model does not change the significance of the SAD-coefficient for the OBX. This suggest that the SAD-effect on returns is not impacted by snow cover for the overall returns on the OSE. The same holds true for the OSESX index.

Amongst the sector indices, we find that it is still only the Energy index that is significantly impacted by the OR, after adding the snow cover variable. Though the significance does not change, the coefficient is just a little more negative when the OR is controlled for snow cover, moving from -0.148 to -0.153. The change is marginal however, and is likely caused by the diminished explanatory power associated with adding more variables to a model.

Looking at Panel B we find that introducing the interaction variable between snow cover and the OR (OR_SC), gives the greatest differences in results between the SAD-model and the OR-model. The perhaps most noteworthy change of them all is that a total of five indices have significant OR-coefficients after introducing the interaction variable between snow and OR. The OBX does now have a significant OR-variable on the 5%-level. And while the OSESX index does not have a significant OR-variable, a total of four sectorial indices does, including the Energy, Materials, Industrials and Finance indices. All of the coefficients are negative, following the expectations set by the SAD-theory. The OR-coefficients in table 5.8 are also roughly the same size as the significant OR-coefficient in table 5.7, ranging from -0.151 to -0.343. This suggest that the SAD might show up in several industries and on the OSE as a whole, and that the effect manifests itself in a similar strength in all significant indexes. If a coefficient increases in significance when introducing another variable to the model as happened for five indices in this case, it could be that the introduced variable captures variations in the OR that kept the original model from being significant. Though only the Energy index had a significant OR-variable in panel A, it showed a more extreme value when the OR_SC variable was introduced, suggesting that snow cover might have had a dampening effect on the disorder as we hypothesized.

Our hypothesis of snow cover dampening the effect that the SAD has on returns are further supported by the signs of the significant interaction variables themselves. While the OBX does not have a significant interaction between OR and snow cover, the OSESX and the sectorial indices Industrials and IT does, and they are all positive. The significant coefficients being positive supports the notion that snow cover could reduce the negative effect that the SAD seems to have on returns, at least on these three indices. Especially noteworthy is that once again one of the indices that had a significant interaction variable were the small-cap index OSESX, which is known for reacting stronger to anomalies compared to other indices. Compared to the low number of significant OR-variables in table 5.8, it seems a lot more probable that the SAD could exist on the OSE when we control for the interaction between OR and snow cover.

In addition to explore alternate specifications when testing hypotheses, we use the OR-model to investigate differences in the resilience of SAD as well. The approach is virtually identical to the one used under chapter 5.3, with the only exception being that the model used has its SAD- and Fall-variables replaced with the OR-variable. We simply investigate whether the significance have changed over time by splitting the data set into two periods. The complete results of these models can be found in table 5.9 to 5.11. Table 5.9 and 5.10 are found in the appendix. Compared to the SAD-model, there is a difference in what indices are significant. While the IT and Health were the ones that seemed significant in the SAD-model, the Energy, Materials and Industrials indexes are significant in the OR-model. In common for both is that results mostly are significant in the period before *Winter Blues* (2003), and are not significant in the period after. The most noteworthy result however is found in table 5.11, which we present here for more detail.

Table 5.11 OR specification with Snow cover and interaction (Mod. 8)

	OBX	OSESX	Energy	Materials	Indus trials	Cons Disc	Cons Stapl	Health	Finan	IT	Tele com	Utilities
Panel A: OR regression with *Snow cover* and *interaction term* for the time period 02.01.1990 – 30.12.2002												
OR	-0.221**	-0.233	-0.290**	-0.396***	-0.243**	-0.126	-0.081	0.137	-0.233**	-0.018	0.304	0.009
	(0.104)	(0.190)	(0.128)	(0.125)	(0.102)	(0.158)	(0.118)	(0.145)	(0.100)	(0.169)	(0.314)	(0.223)
SnoCov	0.016	0.012	0.007	0.005	0.011	-0.030	-0.033	0.052*	-0.013	0.026	0.139*	-0.065
	(0.022)	(0.038)	(0.028)	(0.030)	(0.023)	(0.037)	(0.025)	(0.031)	(0.022)	(0.041)	(0.072)	(0.049)
OR_SC	0.095*	0.124	0.052	0.160**	0.076	0.014	0.070	0.001	0.100**	0.151	0.063	-0.016
	(0.054)	(0.106)	(0.069)	(0.069)	(0.055)	(0.083)	(0.064)	(0.096)	(0.051)	(0.099)	(0.177)	(0.127)
Const.	0.124	0.082	0.177*	0.259**	0.129*	0.402***	0.328***	0.042	0.193***	0.434***	-0.020	0.136
	(0.078)	(0.136)	(0.102)	(0.102)	(0.077)	(0.129)	(0.093)	(0.123)	(0.074)	(0.131)	(0.248)	(0.181)
Obs.	3256	746	3256	3256	3256	3256	3256	3256	3256	3256	1665	1750
Adj. R	0.012	0.041	0.013	0.017	0.013	0.008	0.009	0.004	0.011	0.003	0.011	0.052
F-stat.	2.949	3.613	3.385	4.556	3.005	2.405	3.209	2.095	2.746	1.731	2.051	6.468
Panel B: OR regression with *Snow cover* and *interaction term* for the time period 02.01.1990 - 31.12.2019												
OR	-0.096	-0.095	-0.091	-0.126	-0.089	-0.002	-0.021	-0.050	-0.075	-0.185	-0.017	-0.082
	(0.098)	(0.068)	(0.112)	(0.247)	(0.099)	(0.127)	(0.096)	(0.089)	(0.111)	(0.134)	(0.114)	(0.100)
SnoCov	-0.002	0.029*	-0.002	-0.027	0.009	-0.017	-0.012	-0.000	0.028	0.003	-0.005	0.075***
	(0.023)	(0.015)	(0.027)	(0.069)	(0.022)	(0.032)	(0.023)	(0.021)	(0.024)	(0.033)	(0.029)	(0.024)
OR_SC	0.021	0.073*	0.023	0.094	0.095*	-0.021	-0.044	0.010	0.019	0.116	0.020	0.054
	(0.056)	(0.037)	(0.062)	(0.261)	(0.055)	(0.077)	(0.054)	(0.050)	(0.062)	(0.074)	(0.069)	(0.059)
Const.	0.134	0.067	0.157	0.047	0.158*	0.113	0.162*	0.105	0.017	0.199	0.077	-0.020
	(0.083)	(0.060)	(0.101)	(0.257)	(0.087)	(0.118)	(0.090)	(0.077)	(0.090)	(0.127)	(0.109)	(0.084)
Obs.	4268	4268	4268	4186	4268	4268	4268	4268	4268	4268	4268	4268
Adj. R	0.001	0.027	0.001	0.144	-0.001	0.001	0.002	0.004	0.002	0.003	0.007	0.010
F-stat.	1.123	7.782	0.846	4.861	0.599	0.788	1.078	2.073	1.090	1.367	1.948	3.330
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Returns are presented as daily log returns in percent. The regressions are estimated over the period of 02.01.1990 - 30.12.2019, except OSESX (04.01.2000), Utilities (02.01.1996) and Telecom (06.05.1996).

Controls: Includes the variables of Monday, Tax, Temp, Precip and CloCov.

OR expresses the proportion of people who suffer from SAD (-0,63 to 0,63). *Monday* is a dummy variable controlling for the weekend effect (1 on Mondays, 0 otherwise). *Tax* is a dummy variable controlling for the January effect (1 for the first five and the last trading day of the year, otherwise 0). *Temp* is a control variable measured in Celsius. *Precip* is a control variable measuring precipitation in millimeters. *CloCov* is a control variable measuring Cloud cover in octas, where 0 is clear sky, and 8 is complete cloud cover. SnoCov controls for the amount of snow covering the ground (0 is no cover, 4 is complete cover).

A OR model using the interaction variable between snow cover and OR, and the SnoCov variable (Model 8) result in a total of five indices having significant OR-variables in the pre-2003 period. The OBX displays a significant OR variable at the 5% significance level for the first period, it being non-significant in the second period, suggesting a change in the presence of SAD on the overall market. The OSESX does not have a significant OR-variable for either period. A total of four sectorial indices are significantly reacting to SAD in the pre-2003 period, with Materials being significant on the 1% level and Energy, Industrials and Finance on the 5% significance level. After *Winter Blues* (2003) was published, no indices show signs of the SAD. As far as the snow cover and interaction variables goes, only one snow cover variable is significant and is found in the post-period for the Utilities index. The Interaction variable is significant for two indices in the pre-period and none in the post period.

All in all, it seems like the post-2003 period for the most part, yields fewer significant coefficients in all models, no matter the specification of SAD. One could argue that this supports the theory that SAD has lost much of its effect in the near two decades after *Winter Blues* (2003) was published. This does seem to fit fairly well with the theory of efficient markets, which suggests that investors will implement new information quickly, which will then be reflected in the equity pricing process. Worth noting is that five OR-coefficients being significant in the pre-2003 period, shown in panel B in table 5.11, suggest that the significant results we got in our initial OR-analysis in table 5.8, could be result of an anomaly that was more pronounced in the past.

5.4.2 Fluctuations in liquidity/trading volume

It could be that the few indices we have found to be significantly impacted by SAD so far in reality is influenced by a seasonal variation in liquidity. The table below present the results from model 9 and 10 in panel A and B respectively. In panel A, the SAD_TO interaction variable allows us to see if the effect SAD has on returns, is affected by a marginal change in turnover. If the interaction is not significant, any impact that SAD might have on returns is not likely impacted by turnover. In panel B, we add the SnoCov variable to see if the significance of snow cover changes when controlling for turnover.

As none of the SnoCov variables were significant without the turnover variable (as seen in table 5.3), we are looking for any index to be significant to see if turnover is likely to have an effect on snow cover:

Table 5.12 SAD specification with Turnover (Mod. 9) and Snow cover (Mod. 10)

	OBX	OSESX	Energy	Materials	Indus trials	Cons Disc	Cons Stapl	Health	Finan	IT	Tele com	Utilities
Panel A: Regression controlling for *Turnover* with interaction												
SAD	-0.011	0.040**	0.013	0.066	0.043*	0.038	-0.013	0.011	0.022	0.077**	0.068	0.007
	(0.025)	(0.017)	(0.027)	(0.058)	(0.023)	(0.032)	(0.024)	(0.025)	(0.022)	(0.032)	(0.046)	(0.032)
Fall	-0.083	-0.166**	-0.111	-0.228	-0.152*	-0.143	0.091	-0.124	-0.140	-0.278**	-0.200	-0.084
	(0.081)	(0.073)	(0.094)	(0.186)	(0.083)	(0.115)	(0.089)	(0.097)	(0.085)	(0.123)	(0.180)	(0.113)
TO	53.664***	27.661**	70.088***	80.094***	61.000***	22.958	42.891***	1.806	41.830***	51.596***	8.374	5.053
	(12.051)	(13.419)	(13.910)	(25.682)	(11.253)	(15.586)	(12.386)	(18.203)	(13.211)	(16.017)	(21.740)	(25.615)
SAD_TO	4.867	-4.116	-5.825	-2.433	-5.522	-0.154	-1.410	5.972	-2.235	-5.834	-7.705	2.444
	(6.120)	(3.695)	(6.191)	(9.578)	(5.005)	(6.634)	(5.163)	(5.341)	(4.383)	(6.383)	(10.654)	(7.384)
Const.	-0.054	-0.006	-0.029	-0.249	-0.092	0.076	0.053	0.066	-0.037	0.040	0.030	0.075
	(0.067)	(0.064)	(0.081)	(0.216)	(0.067)	(0.095)	(0.070)	(0.085)	(0.073)	(0.098)	(0.116)	(0.109)
Adj. R	0.008	0.031	0.007	0.113	0.006	0.003	0.004	0.001	0.005	0.004	0.001	0.019
F-stat.	5.090	10.051	5.314	4.316	4.859	2.083	3.248	1.362	3.326	3.169	1.110	5.509
Panel B: Regression controlling for *Turnover* with interaction and *Snow cover*												
SAD	-0.011	0.040**	0.013	0.065	0.042*	0.037	-0.014	0.012	0.022	0.076**	0.069	0.009
	(0.025)	(0.017)	(0.027)	(0.057)	(0.023)	(0.032)	(0.024)	(0.025)	(0.022)	(0.032)	(0.046)	(0.032)
Fall	-0.088	-0.154**	-0.123	-0.251	-0.158*	-0.164	0.068	-0.097	-0.142	-0.296**	-0.174	-0.046
	(0.084)	(0.075)	(0.097)	(0.201)	(0.085)	(0.118)	(0.091)	(0.101)	(0.087)	(0.129)	(0.192)	(0.116)
TO	53.554***	27.942**	69.856***	79.604***	60.871***	22.543	42.421***	2.370	41.775***	51.226***	8.987	5.752
	(12.047)	(13.444)	(13.913)	(25.466)	(11.254)	(15.567)	(12.405)	(18.253)	(13.215)	(15.998)	(21.805)	(25.643)
SAD_TO	4.931	-4.192	-5.684	-2.137	-5.444	0.098	-1.125	5.636	-2.203	-5.612	-7.991	2.042
	(6.138)	(3.705)	(6.226)	(9.576)	(5.039)	(6.653)	(5.188)	(5.388)	(4.401)	(6.420)	(10.714)	(7.381)
SnoCov	-0.005	0.012	-0.010	-0.021	-0.006	-0.018	-0.021	0.024	-0.002	-0.016	0.025	0.036*
	(0.015)	(0.013)	(0.018)	(0.045)	(0.015)	(0.022)	(0.016)	(0.018)	(0.015)	(0.024)	(0.029)	(0.021)
Constant	-0.043	-0.036	-0.005	-0.199	-0.079	0.119	0.101	0.008	-0.031	0.078	-0.029	-0.010
	(0.076)	(0.073)	(0.094)	(0.208)	(0.076)	(0.109)	(0.081)	(0.096)	(0.081)	(0.114)	(0.134)	(0.116)
Adj. R	0.008	0.031	0.007	0.113	0.006	0.003	0.004	0.001	0.005	0.004	0.001	0.019
F-stat.	4.674	9.408	4.876	4.032	4.461	1.966	3.087	1.511	3.049	2.906	1.202	5.302
Obs.	7524	5014	7524	7442	7524	7524	7524	7524	7524	7524	5933	6018
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

$^{*} p < 0.10$, $^{**} p < 0.05$, $^{***} p < 0.01$

Returns are presented as daily log returns in percent. The regressions are estimated over the period of 02.01.1990 - 30.12.2019, except OSESX (04.01.2000), Utilities (02.01.1996) and Telecom (06.05.1996).

Controls: Includes the variables of Monday, Tax, Temp, Precip and CloCov.

SAD is a continuous variable capturing the effect of SAD (0, 6.43). *Fall* is a dummy variable capturing the asymmetry at winter solstice (Sept. 21st to Dec. 21st equals 1, otherwise 0). *Monday* is a dummy variable controlling for the weekend effect (1 on Mondays, 0 otherwise). *Tax* is a dummy variable controlling for the January effect (1 for the first five and the last trading day of the year, otherwise 0). *Temp* is a control variable measured in Celsius. *Precip* is a control variable measuring precipitation in millimeters. *CloCov* is a control variable measuring Cloud cover in octas, where 0 is clear sky, and 8 is complete cloud cover. SnoCov controls for the amount of snow covering the ground (0 is no cover, 4 is complete cover).

In panel A in table 5.12, we find that the TO-coefficient is significant for as many as eight indices, including the OBX and the OSESX. All coefficients are positive, suggesting that turnover has a positive effect on returns. The interaction variable between SAD and turnover is however not significant for any of the indices. This suggests that returns are indeed affected by turnover, but it seems unlikely that any SAD-effect on returns are driven by liquidity related factors.

In panel B we find that the snow cover is not significant for any of the indices. The significance, size and signs on any of the other coefficients in the model are also virtually unchanged compared to the results we got without the snow cover variable, in panel A. In summary, liquidity does not seem to have an impact on the significance of either the SAD-coefficient nor SnoCov.

5.4.3 Fama French three factor model - Seasonal pattern or risk-premium?

The results of our Fama French three factor model are presented in table 5.13:

Table 5.13 Summary of Fama & French 3-factor α for time periods of interest

	OSESX	Energy	Materials	Indus trials	Cons Disc	Cons Stapl	Health	Finan	IT	Tele com	Utilities
α_{Fall}	-0.032	-0.005	0.061	0.048*	0.110**	0.112***	0.071*	0.043	0.127***	0.004	0.052
	(0.032)	(0.033)	(0.070)	(0.028)	(0.045)	(0.033)	(0.037)	(0.032)	(0.049)	(0.026)	(0.048)
α_{Winter}	0.084***	0.168***	-0.093	0.127***	0.141***	0.110***	0.083**	0.170***	0.226***	0.100*	0.055
	(0.029)	(0.032)	(0.134)	(0.028)	(0.046)	(0.031)	(0.041)	(0.031)	(0.047)	(0.059)	(0.045)
$\alpha_{Spring-Summer}$	-0.018	0.057***	0.030	0.060***	0.066**	0.039*	0.035	0.046**	0.061**	0.013	0.030
	(0.021)	(0.020)	(0.046)	(0.017)	(0.028)	(0.020)	(0.026)	(0.020)	(0.029)	(0.015)	(0.032)
Obs.	2530	3793	3779	3793	3793	3793	3793	3793	3793	3005	3034

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Returns are presented as daily log returns in percent. The regressions are estimated over the period of 02.01.1990 - 30.12.2019, except OSESX (04.01.2000), Utilities (02.01.1996) and Telecom (06.05.1996).
The period of fall lasts from September 22nd to December 21st. Winter lasts from December 22nd to March 22nd, while Spring-Summer lasts from March 23rd to September 21st.

Interestingly we can see that all significant alphas no matter what period are positive, which suggests that positive risk-adjusted returns can be earned in a variety of indices during all periods of the year. Three of the indices show significant excess returns during the fall, eight indices show excess returns during the winter and five show excess returns during the spring-summer period.

Though all periods show a positive alpha, we do see a pattern. The winter-alpha is in all cases the largest coefficient when compared to other significant alphas for that index, the only exception being Consumer Staples which just barely has a higher alpha in the fall. We also find that the spring-summer-alpha is lower than during the other periods when compared to other significant alphas. This pattern of excess returns being highest during the winter and lowest during the summer lines up very well with the theory of the SAD-effect and the investment strategy suggested by *Winter Blues* (2003).

When comparing the many significant FF3 alphas to the rather low number of significant coefficients in the results from chapter 5.1, it seems very likely that there is some seasonality in the returns on the OSE. It does however seem unlikely that it is the SAD-effect that is the driver of the seasonal pattern, and it might be that some other phenomenon is behind the excess winter returns.

5.4.4 GARCH - Time varying volatility (GARCH)

Using Engle's Lagrange multiplier test (LM-test) we test for the presence of ARCH effects using five lags. The test indicates ARCH effects for all indices:

Table 5.14 Lagrange Multiplier - Test results

	OBX	OSESX	Energy	Materials	Indus trials	Cons Disc	Cons Stapl	Health	Finan	IT	Tele com	Utilities
SAD/ Fall	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
OR	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: The table shows the p-values for a Lagrange Multiplier test for all indices test using five lags, the p-values indicate the ARCH effect is presented in the models.

Having found significant ARCH effects in all indices, we examine whether time varying volatility may be a reason for changes in returns by applying a General Auto Regressive Conditional Heteroscedastic model (GARCH) with one lag to model time-varying volatility (Bollerslev, 1986). Table 5.15 below, show the results of a GARCH(1,1) model for the SAD-model. The OLS estimates are presented in panel A, panel B show the results of the variance equation associated with the GARCH model, and give a more accurate picture (compared to OLS) of the variables that can vary over time. Panel C show the results on the ARCH and GARCH effects.

Table 5.15 SAD specification (Eq. 2) – GARCH(1,1)

	OBX	OSESX	Energy	Materials	Indus trials	Cons Disc	Cons Stapl	Health	Finan	IT	Tele com	Utilities
Panel A: OLS regression												
SAD	0.005	0.027*	-0.007	0.057	0.023	0.037	-0.018	0.031	0.014	0.057**	0.019	0.015
	(0.016)	(0.014)	(0.018)	(0.044)	(0.016)	(0.023)	(0.017)	(0.020)	(0.016)	(0.024)	(0.016)	(0.022)
Fall	-0.082	-0.164**	-0.107	-0.224	-0.148*	-0.143	0.092	-0.125	-0.138	-0.275**	-0.088	-0.083
	(0.081)	(0.073)	(0.094)	(0.186)	(0.083)	(0.115)	(0.088)	(0.097)	(0.085)	(0.123)	(0.078)	(0.113)
Temp	-0.006**	-0.003	-0.009***	-0.001	-0.003	-0.001	-0.009***	-0.000	-0.005**	-0.006*	0.002	-0.005
	(0.002)	(0.002)	(0.003)	(0.008)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)	(0.004)
Precip	0.003	-0.001	-0.001	-0.003	-0.001	0.004	-0.001	0.001	-0.000	-0.003	-0.010*	-0.001
	(0.003)	(0.003)	(0.004)	(0.008)	(0.003)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.005)
CloCov	-0.012	-0.019**	-0.007	0.000	-0.006	-0.018	-0.008	-0.000	0.005	-0.013	-0.009	0.003
	(0.008)	(0.007)	(0.009)	(0.021)	(0.008)	(0.011)	(0.008)	(0.010)	(0.008)	(0.012)	(0.014)	(0.011)
Const.	0.147***	0.084	0.227***	0.046	0.130**	0.161**	0.211***	0.076	0.116**	0.227***	0.024	0.095
	(0.051)	(0.051)	(0.064)	(0.170)	(0.053)	(0.076)	(0.057)	(0.067)	(0.053)	(0.080)	(0.041)	(0.077)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Variance equation												
SAD	0.001	0.010*	-0.011	0.003	0.005	0.020**	0.000	0.002	0.001	0.006	0.005	-0.000
	(0.006)	(0.006)	(0.008)	(0.010)	(0.006)	(0.010)	(0.007)	(0.008)	(0.006)	(0.009)	(0.005)	(0.008)
Temp	-0.004**	-0.003*	-0.005**	-0.007**	-0.001	-0.001	-0.004**	-0.001	-0.003**	-0.006**	0.000	-0.004
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)
Precip	0.002	-0.001	-0.001	-0.005	-0.002	0.005	0.003	0.004	0.001	0.001	-0.002	0.005
	(0.003)	(0.002)	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.004)	(0.002)	(0.004)
CloCov	-0.006	-0.013**	-0.004	-0.013	-0.003	-0.014	-0.008	0.003	0.003	0.001	-0.002	0.001
	(0.006)	(0.006)	(0.007)	(0.010)	(0.006)	(0.010)	(0.008)	(0.010)	(0.006)	(0.009)	(0.005)	(0.008)
Const.	0.126***	0.149***	0.177***	0.212***	0.106**	0.169***	0.166***	0.081	0.117***	0.185***	0.039	0.094
	(0.038)	(0.038)	(0.049)	(0.066)	(0.043)	(0.058)	(0.048)	(0.054)	(0.040)	(0.057)	(0.031)	(0.058)
Panel C: GARCH(1,1)												
ARCH	0.113***	0.200***	0.071***	0.079***	0.098***	0.070***	0.082*	0.051	0.094***	0.116***	0.095***	0.086***
	(0.013)	(0.035)	(0.010)	(0.015)	(0.014)	(0.023)	(0.048)	(0.043)	(0.015)	(0.024)	(0.018)	(0.028)
GARCH	0.869***	0.746***	0.919***	0.918***	0.875***	0.919***	0.889***	0.942***	0.891***	0.869***	0.894***	0.910***
	(0.015)	(0.037)	(0.012)	(0.015)	(0.018)	(0.028)	(0.075)	(0.054)	(0.019)	(0.025)	(0.020)	(0.029)
Const.	0.037***	0.072***	0.031***	0.048**	0.052***	0.048	0.069	0.031	0.034***	0.084***	0.012***	0.033*
	(0.009)	(0.015)	(0.011)	(0.019)	(0.012)	(0.030)	(0.066)	(0.044)	(0.011)	(0.024)	(0.004)	(0.019)
Obs.	7524	5014	7524	7442	7524	7524	7524	7524	7524	7524	5933	6018

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Returns are presented as daily log returns in percent. The regressions are estimated over the period of 02.01.1990 - 30.12.2019, except OSESX (04.01.2000), Utilities (02.01.1996) and Telecom (06.05.1996).

Controls: Includes the variables of Monday and tax.

SAD is a continuous variable capturing the effect of SAD (0, 6.43). *Fall* is a dummy variable capturing the asymmetry at winter solstice (Sept. 21st to Dec. 21st equals 1, otherwise 0). *Monday* is a dummy variable controlling for the weekend effect (1 on Mondays, 0 otherwise). *Tax* is a dummy variable controlling for the January effect (1 for the first five and the last trading day of the year, otherwise 0). *Temp* is a control variable measured in Celsius. *Precip* is a control variable measuring precipitation in millimeters. *CloCov* is a control variable measuring Cloud cover in octas, where 0 is clear sky, and 8 is complete cloud cover.

From the GARCH(1,1) model we find that almost all indices have significant presence of ARCH and GARCH effects on the 1% level in both the SAD-model and OR-model. The only exception is that a couple of the industry indexes, the Health index and Consumer Staples index show no significance of the ARCH-effect. These coefficients being significant suggest that volatility from previous days affect return in present days. In relation to the SAD, the significant results indicate that a seasonal pattern could be caused by volatility clustering in one period, rather than a behavioral change due to changing daylight. Looking at panel B in table 5.15 we see that it is only the ConsDisc-index in the SAD-specification that shows signs of having a significant SAD-effect after accounting for time-varying volatility.

The variance equation also show that temperature (Temp) seems to have a significant impact on at least half of the indexes, including the OBX along with five sectorial indexes. Few other weather-related variables seem to be significant, suggesting that it is mainly temperature that has an impact on stock returns on the OSE. All significant Temp-coefficients are negative, suggesting that an increase in temperature has a negative impact on returns.

5.5 Other possible explanations for our results

As discussed under the literary review, academic literature on risk aversion suggest a positive link between depression or anxiety and risk aversion. This means that not only changes in light exposure, but *any* event that could either increase- or provide relief to depression or anxiety, could impact risk aversion, and thus returns. In the following, we explore a few alternative explanations as to why we might have found the results we did. Note that these explanations could sometimes apply to both our hypotheses.

5.5.1 Winter sports – A remedy for depression and explanation to positive SAD-returns?

Research on social psychology find a strong relation between loneliness and depression. Some of the non-medical treatments or activities suggested for people undergoing depression are exercising and being active, reducing isolation as much as possible and rather focus on spending time with other people (Weeks et al., 1980; Steger & Kashdan, 2009; National Institute of Mental Health, 2021). With the arrival of snow each year there is a surge in live- and televised winter sports competitions in Norway. This could impact the returns on OSE in several different ways.

The typical duration of the organized ski season in Norway lasts from around the 20th of November and ends around mid- to late March (Skiforbundet, 2021). This period is a close match to the winter-half of the SAD-period (December 21st – March 21st), the period in which returns seem to experience a boost compared to the more moderate returns that tend to occur during the fall-half. Winter sports are quite a big deal in Norway and generally a time causing a sense of joy, excitement, community, gathering and celebration. As such, it might be that at least some of the reduction observed in the seasonal depression around winter, as suggested by the SAD-theory and our significant results in chapter 5, could in fact be explained by treatment-related factors associated with *winter sports,* rather than more daylight.

In addition to the social and entertaining aspect of winter sports, a lot of Norwegians spend the winter outdoors performing various snow-related activities themselves. As mentioned, physical activity is one of the suggested remedies for depression. Rosenthal (2012) refers to evidence of exercise having a beneficial effect on mood for those who suffer from depression, including those suffering from SAD. Then there is the combination of both exercise and increased light exposure associated with performing winter sports outdoors on a bright winter day, making it even more difficult to separate the different curative effects apart (Rosenthal, 2012).

In short, the theory of SAD assumes that depression cause below average returns in the fall. It is however less clear what cures such a depression, resulting in above average returns in the winter period. The theory of SAD assumes that it is the increase in sunlight after winter solstice that cures it. However, it could be that the depression is cured by curative effects related to winter sports rather than increased sunlight. Though winter sports could help alleviate depression, involving both physical activity and exposure to light, it makes it more difficult for us to separate between the physical benefits and the benefits related to light exposure. It is possible that the positive results we got on the SAD and OR variables are not due to changing hours of daylight, but increased joy and physical activity.

5.5.2 Insignificant results on snow cover – A result of omitted variables?

Our results suggest that there is no significant relation between snow cover and SAD-related returns. While it might be the case that snow cover actually has no impact on SAD-returns, the lack of significance could also be a result of snow cover being affected by other factors that were not properly controlled for in our regressions. There are a couple of explanations that seem somewhat relevant to this hypothesis.

Much of what was said about winter sports and SAD-related returns could go for the relation between SnoCov and SAD as well. In a typical year, the first snow in Oslo is observed around mid-November, which naturally is pretty close to when the winter sports season starts (YR, 2015).

While winter sports are hypothesized to have a *positive* correlation with both snow cover and returns, snow cover is also likely to be related to *snowfall,* which some argue could influence trading volume. Loughran & Schultz (2004) hypothesized that snowfall will make it more difficult or slower to get to work. In periods with a great amount of snowfall, it is not uncommon that vehicles get stuck in the snow, public transport gets packed or delayed, or the roads get jammed. Heavy snowfall may also encourage people to leave work earlier to get ahead of traffic. With investors spending less time at their desks and stockbrokers off work, there's less time for trading and the trading volume is likely to decline. Loughran & Schultz found that for cities experiencing blizzards (more than 8 inches of snowfall), the trading volume falls more than 17% on the day of the snowstorm and almost 15% the following day. Though most days with snowfall are probably not caused by a blizzard (Loughran & Schultz, 2004). In addition to lower trading volume, some have found evidence that market returns are significantly lower on days with unexpectedly high traffic (Imisiker et al., 2019).

A possible explanation as to why we did not find any significant results on the SnoCov variable is that snow simply affects the SAD in many different ways, some having a positive impact and others a negative impact. There might simply be too many variables correlating with snow that was not controlled for in the models, resulting in too much noise in the SnoCov variable to find a significant pattern. Amongst other things, snow cover could increase exposure to light or provide joy in form of winter sports, but it could also lead to increased traffic and stress, or even a sense of displeasure having to work on an otherwise bright and snowy day.

5.6 Trading strategies

Our results suggest that only a couple of indices on the OSE are significantly impacted by the SAD. Those who were significant however support the SAD-theory as it is presented in *Winter Blues (*2003), suggesting that the same trading strategy that was explored and found profitable in Winter Blues, might be profitable here as well. This is further supported by our Fama/French model which showed that significant alphas in the both the winter and fall period tended to have higher excess returns than the spring-summer period. Based on this we compose a couple of trading strategies to explore whether SAD-related patterns can yield returns in excess of the market.

Most papers concerning the SAD base their strategy on the one presented in *Winter Blues* (2003), which make portfolio adjustments twice a year, in sync with when the SAD-effect beings and ends. Using this approach, they report that the most successful strategy is to be *long* during the SAD-period (fall-winter), and *short* or *out* of the market during the spring-summer period (Kamstra et al., 2003). The strategy presented in *Winter Blues* (2003) involves swapping markets each time the SAD-period ends. For example, the authors propose to stay in the Swedish market for the northern-hemisphere fall-winter, then sell and reinvest in the Australian market for the southern-hemispheres fall-winter. Essentially chasing the SAD-effect around the globe. As we focus on the Norwegian market only, we propose being invested in risk free assets when not holding risky assets (Kamstra et al., 2003).

One of the benefits of such a strategy is that it is simple to understand, takes very little effort to execute and is cost-efficient. Making portfolio changes only twice a year, trading costs and tax on profits are relatively low which increases the likelihood of a profitable strategy. In this paper we will however do as *Winter Blues* (2003) and look away from trading costs and taxes to simplify the process (Kamstra et al., 2003). Other papers on seasonal anomalies have utilized a very similar strategy (Guo et al., 2014; Guan & Saxena, 2015). We also propose a few new strategies based on the results we got from running our models. A list of all the trading strategies we investigate is shown in table 5.16:

Table 5.16 Trading strategies – How they work and performed

Name	In market	Risk-free rate	Description
Benchmark	100%	-	Holding the index
Pro SAD	100% if fall/winter 0% otherwise	0% if fall/winter 100% otherwise	Invested in risky assets when SAD is in effect
Excluding Fall	0% if fall 100% otherwise	100% if fall 0% otherwise	Excluding period where SAD affects return negatively
Pro winter	100% if winter 0% otherwise	0% if winter 100% otherwise	Invested in risky assets when effects of SAD reduce

To start off we generate a benchmark buy-and-hold strategy of simply holding the given index. We then test three different SAD-related trading strategies and compare them to the returns yielded by this benchmark.

The first strategy we propose is a *Pro-SAD* strategy which is basically the same as the original one from *Winter Blues* (2003), suggesting to be long in the market during the full SAD-period. The two latter strategies are slightly different however, and are based on our own results. Our second strategy is *a Fall-excluding* strategy where we go long in the market from December 21st to September 21st, basically being out of the market during the fall period where negative SAD-effects are theorized to be the strongest. The third and final strategy is *Winter-only,* based on staying in the market only during the winter-period from December 21st to March 21st, where the curative effects of SAD shifts people from being risk averse to being more inclined to take risks again. The idea being that these three months capture a period where people gradually become more inclined to take risk again, which boost the overall demand for stocks and should have a positive impact on stock prices.

Table 5.17 show the daily mean returns based on the full length of observations for each index in column *Daily.* The remaining columns show the mean returns for their respective period. The choice of columns included is based on the results from chapter 5.

Table 5.17 Daily percentage mean returns for the different periods

	Mean returns					
Indices	Daily	Fall	Winter	Spring/ Summer	Fall/ Winter	Dec- Sept
OBX	0.0279	-0.0044	0.0987	0.0081	0.0480	0.0392
OSESX	0.0158	-0.0201	0.0992	-0.0067	0.0387	0.0284
Energy	0.0641	-0.0113	0.1633	0.0509	0.0775	0.0905
Materials	0.0420	0.0675	0.0123	0.0412	0.0428	0.0333
Industrials	0.0760	0.0496	0.1283	0.0609	0.0913	0.0852
Consumer discretionary	0.0950	0.1100	0.1354	0.0676	0.1229	0.0898
Consumer staples	0.0776	0.1139	0.1079	0.0419	0.1138	0.0648
Health	0.0705	0.0844	0.1018	0.0468	0.0945	0.0656
Finance	0.0784	0.0431	0.1778	0.0471	0.1101	0.0907
IT	0.1143	0.1253	0.2160	0.0587	0.1708	0.1104
Telecom	0.0477	0.0306	0.0799	0.0444	0.0512	0.0538
Utilities	0.0530	0.0642	0.0646	0.0416	0.0646	0.0491

Table 5.18 show the mean annual returns for the benchmark and the suggested trading strategies. At first glance, we see that both the OBX total return index and the OSESX small-cap index have positive excess returns for all strategies. It does however seem as our suggested new strategies beat not only the benchmark, but the *Winter Blues* (2003) pro-SAD strategy as well.

Both indices had their highest returns in the newly proposed *Winter-only* strategy with excess annual returns of 2.582 percent for the OBX and 5.661 percent for the OSESX. The Fall-excluding strategy seem more mixed as a strategy. It beats the pro-SAD strategy for the OBX with annual excess returns of 1.558 percent, but the pro-SAD beat the OSESX small-cap index, though not by much. These results fit well with our expectations based on the results both from the regression models and the Fama/French model.

Most of the industry indices however do not beat the buy-and-hold strategy in any of the SAD-inspired strategies. The Energy index is the only one that somewhat sticks out, with both of our suggested new strategies being superior to the pro-SAD. Only the Fall-excluding strategy yield excess returns however. The remaining sectorial indices are unable to provide excess returns, and it seems reasonable to recommend a buy-and-hold strategy for these indices.

Table 5.18 Annual total and excess returns for each strategy

	Total returns				Excess returns		
Indices	Buy-and-hold	Pro-SAD	Fall excluded	Winter only	Pro-SAD	Fall excluded	Winter only
OBX	7.029	8.271	8.587	9.611	1.242	1.558	2.582
OSESX	3.984	7.095	6.545	9.645	3.111	2.561	5.661
Energy	16.154	11.988	18.282	13.684	-4.166	2.129	-2.469
Materials	10.576	7.606	7.476	4.168	-2.970	-3.100	-6.408
Industrials	19.148	13.726	17.288	11.480	-5.422	-1.860	-7.668
ConsDisc	23.948	17.704	18.152	11.928	-6.244	-5.796	-12.020
ConsStap	19.546	16.563	13.438	10.195	-2.983	-6.109	-9.351
Health	17.761	14.131	13.581	9.808	-3.630	-4.180	-7.953
Finance	19.750	16.094	18.327	14.599	-3.656	-1.424	-5.151
IT	28.797	23.741	22.048	17.001	-5.056	-6.749	-11.796
Telecom	12.029	8.668	11.356	8.428	-3.361	-0.673	-3.601
Utilities	13.365	10.364	10.468	7.468	-3.000	-2.896	-5.897

Notes: The benchmark strategy is showed in the first column *Daily,* where we hold the portfolio through the year. For the investment strategy we hold the portfolio for the period of December 21st to September21st, where we exit the market and yield risk-free return for the period of September 22nd to December 20th.
Excess returns are the excess over the Benchmark strategy.

6 Summary

In this thesis we have explored whether returns on Oslo Stock Exchange are significantly affected by the Seasonal Affective Disorder, using the OBX total return index, the OSESX small-cap index and ten sectorial indices. Evidence provided in this paper indicate that the SAD have significantly impacted returns on some specific indices on OSE in the period 1990-2019.

Applying Ordinary Least Squares method, we find that neither the OBX nor the OSESX are likely to be significantly affected, using both a baseline SAD-specification of the disorder and a more behavioral Onset/Recovery-specification. Only when analyzing specific sectorial indices do we get results suggesting that the IT-index is significantly impacted when using the baseline SAD-model (daily impact of +0.057 percent during winter period), and the Energy index when using the Onset/Recovery model (daily impact of -0.148 percent during entire period). Though only one index is significantly impacted by SAD in either model, their results unanimously follow the established theory of the SAD-effect, with returns in the winter being positively affected by the disorder and returns in the fall being negatively impacted.

Further, using the baseline SAD-model we find that snow cover does not initially seem to have any significant impact on the SAD-effect on the OSE. However, using a model that puts more emphasis on human behavior - the OR-model, we find that snow cover dampens the negative impact the OR-variable otherwise have on returns for the OSESX, Industrials and IT indexes, as suggested by the positive signs on all significant snow cover/SAD interaction variables. In addition, using the OR-model as many as five indices seem to have their returns significantly impacted by the disorder when accounting for the interaction between snow cover and the SAD. This includes the OBX total returns index representing the overall returns on the OSE, suggesting that the SAD might affect returns on the OSE at large.

The Fama French three factor model and various seasonal trading strategies suggest that there is indeed some kind of seasonal pattern in the returns on the OSE, and that this pattern is in line with the theory of SAD. Various robustness checks suggest that variations in turnover is not likely to explain any pattern we found, where as a GARCH(1,1) model imply that volatility have a systematic pattern and could as such be one possible explanation for a seasonal pattern in returns. It also seems that the SAD might have been more present in the period before 2003, when the anomaly rapidly got more cover with the paper *Winter Blues* (2003) putting it in the spotlight.

Though we make an effort to make our results as robust as possible, there is a limit to the accuracy of our methods, what the results of our models can really tell us, and who the results apply to even if they prove to be significant. Due to rapid digitalization the past decades, the stock market is almost incomparable to what it was at the time of the standard-setting papers such as *Winter Blues* (2003). Today trading can happen instantly and virtually anywhere where there is a phone reception. This significantly reduces the information that can be interpreted from both the SAD and weather data, affecting both our hypotheses. Traders could find themselves in a different hemisphere experiencing daylight patterns related to a summer period, while trading in a market experiencing winter. Weather data is even more location specific and can quickly change from one minute to another, even if traders are exposed to the weather from the relevant area. In addition, we cannot know where any investors have found themselves either at when they made their trade, or the time leading up to when they made their investment decisions. Thus, we assume that traders were exposed to the sunlight variations and the weather variations that occurred at OSE. More accurate results could likely be derived with geographical knowledge of when and where each trade took place, and with weather data measured at a higher frequency than daily observations. We have not been able to get hold of such data however and use completely anonymous data from the OSE in this paper.

Despite some limitations, these results can be useful in several ways. Knowing that some indexes react significantly to the SAD, investors can make more rational investment decisions, or avoid investment options that may be prone to react to the SAD. The results also provide a greater understanding of what forces may influence market movements on various indices and the OSE in general. In addition, the results have proven to provide great fuel for trading strategies that yield returns in excess of the market. Our data suggesting as much as 5.6 percent yearly in excess of a buy-and-hold market strategy could be earned. And all in all, greater awareness of the SAD and how it influences returns on OSE could result in a more efficient stock market.

For future research, it could be interesting to see if more accurate data on both weather and investor location could be obtained to get more accurate results. An alternate angle on data could be to compare private versus institutional investors to see if professionals are less influenced by the SAD than private investors. Another suggestion could be to include some more variables related to snow to the regression models. Maybe years with Olympic winter games or seasons with a great number of days with snow could have an impact on both SAD and returns.

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Appendix

Table 5.9 OR specification (Mod. 2) splitting the dataset

	OBX	OSESX	Energy	Materials	Indus trials	Cons Disc	Cons Stapl	Health	Finan	IT	Tele com	Utilities
Panel A: OR regression, 02.01.1990 – 30.12.2002												
OR	-0.141*	-0.113	-0.244**	-0.233**	-0.177**	-0.072	0.035	0.070	-0.111	0.108	0.195	0.076
	(0.085)	(0.168)	(0.105)	(0.103)	(0.084)	(0.127)	(0.098)	(0.134)	(0.080)	(0.139)	(0.267)	(0.190)
Const.	0.121*	0.056	0.173**	0.214**	0.123*	0.343***	0.245***	0.135	0.136**	0.430***	0.195	0.027
	(0.066)	(0.130)	(0.087)	(0.087)	(0.066)	(0.110)	(0.078)	(0.110)	(0.064)	(0.115)	(0.216)	(0.164)
Obs.	3256	746	3256	3256	3256	3256	3256	3256	3256	3256	1665	1750
Adj. R	0.012	0.041	0.013	0.016	0.013	0.008	0.008	0.004	0.010	0.003	0.010	0.052
F-stat.	3.474	4.424	4.160	5.253	3.651	2.904	3.385	2.126	2.817	1.981	1.641	7.477
Panel B: OR regression, 02.01.1990 - 31.12.2019												
OR	-0.072	-0.058	-0.064	0.013	0.000	-0.000	-0.051	-0.039	-0.094	-0.066	0.011	-0.129
	(0.083)	(0.057)	(0.093)	(0.280)	(0.084)	(0.108)	(0.081)	(0.077)	(0.093)	(0.115)	(0.100)	(0.086)
Const.	0.124*	0.092*	0.146*	-0.033	0.140*	0.090	0.156**	0.101	0.058	0.164	0.061	0.090
	(0.071)	(0.053)	(0.088)	(0.246)	(0.076)	(0.099)	(0.077)	(0.066)	(0.078)	(0.105)	(0.093)	(0.073)
Obs.	4268	4268	4268	4186	4268	4268	4268	4268	4268	4268	4268	4268
Adj. R	0.001	0.027	0.001	0.145	-0.001	0.001	0.002	0.004	0.002	0.003	0.008	0.008
F-stat.	1.377	8.887	1.048	5.917	0.337	0.929	1.300	2.577	1.208	1.303	2.382	3.145
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

$^{*}\,p < 0.10$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$

Returns are presented as daily log returns in percent. The regressions are estimated over the period of 02.01.1990 - 30.12.2019, except OSESX (04.01.2000), Utilities (02.01.1996) and Telecom (06.05.1996).

Controls: Includes the variables of Monday, Tax, Temp, Precip and CloCov.

OR expresses the proportion of people who suffer from SAD (-0,63 to 0,63). *Monday* is a dummy variable controlling for the weekend effect (1 on Mondays, 0 otherwise). *Tax* is a dummy variable controlling for the January effect (1 for the first five and the last trading day of the year, otherwise 0). *Temp* is a control variable measured in Celsius. *Precip* is a control variable measuring precipitation in millimeters. *CloCov* is a control variable measuring Cloud cover in octas, where 0 is clear sky, and 8 is complete cloud cover. SnoCov controls for the amount of snow covering the ground (0 is no cover, 4 is complete cover).

Table 5.10 OR specification (Mod. 2) with Snow cover splitting the dataset

Panel A: OR regression with *Snow cover* for period 02.01.1990 – 30.12.2002

	OBX	OSESX	Energy	Materials	Indus trials	Cons Disc	Cons Stapl	Health	Finan	IT	Tele com	Utilities
OR	-0.142	-0.128	-0.247**	-0.263**	-0.180**	-0.114	-0.023	0.137	-0.150*	0.107	0.351	-0.005
	(0.087)	(0.165)	(0.108)	(0.107)	(0.086)	(0.134)	(0.100)	(0.132)	(0.083)	(0.147)	(0.271)	(0.193)
SnoCov	-0.001	-0.011	-0.002	-0.023	-0.002	-0.032	-0.045**	0.052*	-0.030	-0.001	0.127*	-0.062
	(0.019)	(0.037)	(0.025)	(0.026)	(0.020)	(0.032)	(0.022)	(0.030)	(0.019)	(0.035)	(0.068)	(0.043)
Const.	0.123	0.075	0.176*	0.256**	0.128*	0.402***	0.327***	0.042	0.191**	0.431***	-0.020	0.136
	(0.078)	(0.135)	(0.102)	(0.102)	(0.077)	(0.129)	(0.093)	(0.123)	(0.074)	(0.131)	(0.248)	(0.181)
Obs.	3256	746	3256	3256	3256	3256	3256	3256	3256	3256	1665	1750
Adj. R	0.011	0.040	0.013	0.016	0.012	0.008	0.009	0.004	0.010	0.002	0.012	0.053
F-stat.	3.093	3.950	3.702	4.722	3.245	2.651	3.398	2.310	2.767	1.770	2.221	7.075

Panel B: OR regression with *Snow cover* for period 02.01.2003 – 30.12.2019

	OBX	OSESX	Energy	Materials	Indus trials	Cons Disc	Cons Stapl	Health	Finan	IT	Tele com	Utilities
OR	-0.079	-0.037	-0.073	-0.050	-0.013	-0.019	-0.056	-0.042	-0.060	-0.093	-0.001	-0.039
	(0.084)	(0.059)	(0.097)	(0.258)	(0.086)	(0.111)	(0.082)	(0.077)	(0.095)	(0.116)	(0.099)	(0.088)
SnoCov	-0.006	0.015	-0.006	-0.046	-0.009	-0.013	-0.004	-0.002	0.024	-0.019	-0.009	0.064***
	(0.020)	(0.013)	(0.023)	(0.071)	(0.020)	(0.029)	(0.021)	(0.019)	(0.022)	(0.029)	(0.025)	(0.021)
Const.	0.134	0.065	0.157	0.046	0.157*	0.113	0.163*	0.104	0.017	0.198	0.076	-0.021
	(0.083)	(0.060)	(0.101)	(0.257)	(0.087)	(0.118)	(0.090)	(0.077)	(0.090)	(0.127)	(0.109)	(0.084)
Obs.	4268	4268	4268	4186	4268	4268	4268	4268	4268	4268	4268	4268
Adj. R	0.001	0.027	0.001	0.145	-0.001	0.001	0.002	0.004	0.002	0.003	0.007	0.010
F-stat.	1.236	8.086	0.938	5.280	0.318	0.870	1.156	2.296	1.202	1.187	2.121	3.511
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Returns are presented as daily log returns in percent. The regressions are estimated over the period of 02.01.1990 - 30.12.2019, except OSESX (04.01.2000), Utilities (02.01.1996) and Telecom (06.05.1996).

Controls: Includes the variables of Monday, Tax, Temp, Precip and CloCov.

OR expresses the proportion of people who suffer from SAD (-0,63 to 0,63). *Monday* is a dummy variable controlling for the weekend effect (1 on Mondays, 0 otherwise). *Tax* is a dummy variable controlling for the January effect (1 for the first five and the last trading day of the year, otherwise 0). *Temp* is a control variable measured in Celsius. *Precip* is a control variable measuring precipitation in millimeters. *CloCov* is a control variable measuring Cloud cover in octas, where 0 is clear sky, and 8 is complete cloud cover. SnoCov controls for the amount of snow covering the ground (0 is no cover, 4 is complete cover).